MUSICAL NETWORKS

THE CASE FOR A NEURAL NETWORK METHODOLOGY IN ADVERTISEMENT MUSIC RESEARCH

HANNELORE OLIVIER

Pectora roborant cultus recti

Thesis presented in partial fulfilment of the requirements for the degree of Master of Philosophy in Music Technology in the Faculty of Arts, University of Stellenbosch.

April 2005

Supervisors:
Mr. T Herbst
Prof. M Smit

DECLARATION

I, the undersigned, hereby declare that the work contained in this thesis is my own original work and that I have not previously in its entirety or in part submitted it at any university for a degree.

Signature:

Date: **20 November 2004**

SUMMARY

Countless scientists had been struggling for centuries to find a significant connection between cognition, emotion and reasoning – resulting in today's rather embarrassingly imperfect understanding of even the most basic human cognition. We should apprehend that it is unlikely that major breakthroughs in the Cognitive Sciences, Psychology, Sociology or the Medical Sciences will elucidate everything about the human brain and -behaviour in the very near future. Realizing this, it is realistic that we should transfer our attention to things that we do know and understand, and reconsider the power that lies in the integration of results and an interdisciplinary perspective in research. Using the tools we have to our disposal today – digital tools such as ANNs which did not exist a few decades before – this is actually readily viable today.

This thesis demonstrates that it is possible to break the traditional boundaries that have periodically prevented the Humanities and the Natural Sciences to join forces towards a greater understanding of human beings. By using ANNs, we are able to merge data from any subfield within the Humanities and Natural Sciences in a single study. The results, interpretations and applications which could develop from such a study would certainly be more inclusive than those derived from research conducted in one or two of these fields in isolation.

Sufficient evidence is provided in this dissertation to support a methodology which employs an artificial neural network to assist with decision-making processes related to the choice of advertisement music. The main objective of this endeavour is to establish the feasibility of combining data from many diverse fields, in the creation of an ANN that can be helpful in research regarding South African advertisement music. The thesis explores the notion that knowledge from many interdisciplinary study fields ought to play a leading role in the creation and assessment of effective, target-group-specific advertisement music. In obtaining this goal, it examines the probability of producing a computer-based tool which can assist people working in the advertising industry to obtain an educated match between product, consumer, and advertisement music.

Taking a multidisciplinary point of view, the author suggests a methodology for the design of a digital tool in the form of a musical network model. It is concluded that, by using this musical network, it is indeed possible to guarantee a functional musically-paired commercial, which effectively addresses its target-group and has an appropriate emotional effect in support of the marketing goals of the advertising agent.

The thesis also demonstrates that it is possible to gain new insights regarding a fairly unstudied discipline, without necessarily conducting new research studies in the specified field. The thesis proves that - by taking an interdisciplinary approach and by using ANNs - it is possible to attain new data that is scientifically valid, even in an unacknowledged field such as South African advertisement music.

Although the scope of the thesis does not provide for the actual implementation of the musical network, the feasibility of the conceptual idea is thoroughly examined, and it is concluded that the theory in it’s entirely is definitely feasible, and can be implemented in a future study.

OPSOMMING

Vir eeue al probeer wetenskaplikes 'n betekenisvolle verwantskap tussen denke, emosie en redenasie vind. Nietemin het ons vandag slegs 'n beperkte begrip van selfs die mees basiese menslike kognisie. Ons moet besef dat dit onwaarskynlik is dat deurbrake in die Kognitiewe Wetenskappe, Sielkunde, Sosiologie of die Mediese Wetenskap in die nabye toekoms die volle funksionaliteit van die menslike brein en gedrag sal bekendmaak. Met inagname hiervan, is 'n aandagsverskuiwing geoorloof - na die dinge wat ons wel weet en verstaan. Die enorme potensiaal opgesluit in die integrasie van resultate en 'n interdissiplinêre navorsingsperspektief behoort gevolglik heroorweeg te word. Ons beskik tans oor meer as voldoende digitale hulpbronne, waaronder kunsmatige neurale netwerke, wat wel so 'n benadering kan bewerkstellig.

In hierdie tesis word daar gedemonstreer dat dit moontlik is om die grense wat tradisioneel 'n samewerking tussen die Geestes- en Natuurwetenskappe beperk het, af te breek - 'n werkswyse wat noodwendig sal lei tot 'n beter begrip van die mens. Kunsmatige neurale netwerke maak dit moontlik om navorsingsdata uit die Geestes- en Natuurwetenskappe te kombineer in 'n enkele onderneming. Die bevindinge, interpretasies en toepasings wat potensieel uit so 'n metodologie sou kon voortspruit, is sonder twyfel meer omvattend as dié afkomstig vanuit 'n eendimensionele studie.

Voldoende bewyse word deur die loop van hierdie studie voorgehou ter ondersteuning van 'n kunsmatige neurale netwerk-metodologie in die assistering van besluitnemingsprosesse rakende advertensiemusiek. Die hoofdoelwit van die onderneming is om te toets of die ontwerp van 'n kunsmatige neurale netwerk - deur die kombinasie van data uit diverse studierigtings - wel geoorloof en funksioneel sou kon wees. Die aanname dat inligting uit 'n aantal interdissiplinêre studierigtings 'n prominente rol behoort te speel tydens die skep en beoordeling van effektiewe, teikengroep-gerigte advertensiemusiek, word gevolglik ondersoek. Om hierdie objektief te bewerkstellig, word die waarskynlikheid bestudeer na die ontwerp van 'n rekenaargebaseerde hulpbron - wat mense in die advertensiewese behulpsaam kan wees om 'n berekende en ingeligte keuse uit te oefen om produk, verbruiker en advertensiemusiek te laat pas.

Die outeur benader die probleem vanuit 'n multidissiplinêne oogpunt, en stel 'n werkswyse voor vir die ontwerp van 'n digitale hulpbron – in die vorm van 'n musikale netwerk model. Daar word bevind dat - deur die gebruik van die voorgestelde model, dit wel moontlik is om die funksionaliteit van 'n musiek-gepaarde advertensie te verseker. Verder word daar gedemonstreer dat nuwe insigte rakende 'n grotendeels afgeskeepte studierigting soos Suid-Afrikaanse advertensiemusiek moeiteloos bekom kan

word, sonder om noodwendig navorsing binne die spesifieke gebied te loods. Laasgenoemde is doenbaar deur 'n interdissiplinêre navorsingsbenadering, gekombineerd met 'n kunsmatige neurale netwerk-metodologie.

Die omvang van hierdie studie maak nie voorsiening vir die implementering van die musikale netwerk nie. Nietemin word die werkbaarheid van die konseptuele idee in diepte ondersoek, met die gevolgtrekking dat die teorie in sy geheel sonder twyfel prakties is, en in 'n toekomstige studie geïmplementeer kan word.

Vir Susan en Johan Olivier

Doen alles asof dit van jouself afhang

Bid asof dit van God afhang

TABLE OF CONTENTS

INTRODUCTION

Suppose you decide to instigate a business endeavour and can afford only a single device to assist in this intricate task. Your tool should be able to select your company's location, stock and employees, as well as to anticipate the likelihood of their committing any white collar crime. The device must control your production processes, anticipate the expected product choices of your customers, calculate the consequences of your advertising strategies on them, and predict your sales for the first ten years. It should be able to assess your risks involved, calculate the possibility of bankruptcy or the probability of a merger with a neighbouring company, and select the best legal strategies if you should go to court. The same tool is capable of modelling the way in which you obtain business-related information, reveal your personal style of decision-making, and evaluate events in the local government's international relations which could possibly affect your company.

In addition to this, the device is able to analyse your executives' voting behaviour in the upcoming managerial election, diagnose you or your marketing director as having a psychiatric disorder, and decide on the best medical treatment option for the both of you. It can forecast tomorrow's weather and the probability of you winning the national lottery, predict the stock market, assist in the development of a vehicle with a vision system which allows it to negotiate obstacles, recognize handwritten digits, automatically compile indexes of sound databases and compose and harmonize new songs. Besides these few applications, the specified tool can also compress images, manage the battlefield, learn the correct pronunciation of the English language, and explain patterns of social mobility and inequality. However, if you feel your modest tool to be a bit inadequate in its applicational value, you can always use it to detect and measure the chewing and rumination intervals of sheep by analysing jaw sounds transmitted through their heads, following after the example of Zaknich & Baker (1998).

If such a device was possible at all, surely it is not too farfetched to presume that it can be used to select the most appropriate advertisement music for your company's new television commercial. This tool is real, and labelled as an artificial neural network.

BACKGROUND

Advertising is the means by which one party tries to persuade another into purchasing a particular product or service (Huron (1989: 557). Advertising is directed towards a very broad and general audience, therefore it depends completely on *mass media* and consequently on *widespread social meanings rather than personal or idiosyncratic motivations for purchasing.*

In one of a very few available publications on the subject of advertisement music*,* Woodward makes certain assumptions about *good* advertising music: it attracts the consumer's attention, creates a certain mood or atmosphere, lies within the musical taste of the main consumer demographic, and will be remembered. Furthermore, the author states that *...these elements (contain) no musical terms, definitions, or instructions. (One) reason for this is that there are no musical formulas, styles, or techniques that will guarantee you a good musical commercial* (Woodward, 1982:17).

Woodward's rather unacademical account of functional advertisement music reflects the general lack of scientifically valid and reliable research in the field of music used for commercial purposes. The author's view seems to hold some credibility in the sense that up to now there has been no foolproof recipe subjacent to the composition of music which will optimally support the marketing of a distinctive product. Nevertheless, it is admissible to question Woodward's comment, as the researcher will do in the following hypothesis:

> **Functional commercial music can to a certain extent be guaranteed - in musical terms and through the application of well-considered and empirically proven musical elements – in a specified context.**

A *specified context* refers to advertisement music aimed at the South African multicultural society, and by *functional commercial music* the following is implied:

- music which has relevance to, and is in fitting with, a unique product;
- music which plays a supportive, complementary part in advertising a product;
- music which effectively addresses the target-group - in that it has the relevant emotional effect on the specific culturally-specified target population which fits the marketing goals of the advertising agent.

Working from a multidisciplinary perspective, the research endeavour aims at proving that scientific research findings from the fields of Psychology of Music, Consumer Science and the Cognitive Sciences could (and should) play a major role in the composition and assessment of effective, target-group-specific advertisement music. It will do so by mainly drawing on research previously conducted in the specified areas of study, but with a distinctive application, thus making the thesis an explorative pilot study. The possibility of creating a computer-based resource tool in this connection (which could serve as an aid to people working in the advertising industry) will also be examined. The tool considered in this aspect is an artificial neural network – a computer software program applied to a framework of musical pattern recognition.

Broadly stated, the focus of the research project is to study the impact of South African television advertising music on the consumer. It encompasses an inquiry into the purposeful use of emotion in advertisement music, with the objective to determine the effect thereof on diverse cultural groups. This will be done with reference to cultural norms, consumer studies and individual differences in cognitive and emotional perception. More specifically, the study addresses the following research questions:

1. Do various cultural groups in South Africa reveal homogeneous patterns of affective reactivity to South African television advertisement music?
2. If so, is this reaction in fitting with the goal of the advertisement?
3. Based on the knowledge of these goals, can universals be established in the emotional response of homogeneous cultural groups to advertisement music?
4. If so, could this knowledge, applied in a music technological context, be helpful in the assessment and composition of functional advertisement music?

RATIONALE

As previously mentioned, the thesis will focus on South African television advertisement music and deficiencies identified in the process of addressing target populations. The rationale of the study firstly lies in a noticeable void in research and / or application of results within this field - specifically aimed at a multicultural society. Unique to this study is the interdisciplinary nature thereof, with theoretical premises derived from the fields of the Cognitive Sciences, Consumer Sciences and Psychology. Also, the application of the research findings in a music technological context is unparalleled in previous studies.

The ultimate object and final rationale of the thesis is that the outcome of the research could be used in the creation of a computer-based software tool aimed towards the assessment of cultural-specific, target-group orientated, goal-directed television advertising music. This faculty will be examined in depth in the application part of the thesis.

As stated before, the aim of the thesis is to study the effect of South African television advertisement music on the consumer. The goal is to establish the effect of emotion as manifested through advertisement music on diverse cultural groups with reference to cultural norms, consumer research and individual differences in cognitive perception. The following hypotheses will be investigated:

1. Different cultural groups in South Africa reveal homogeneous patterns of affective reactivity to South African television advertisement music.
2. This reaction is in fitting with the goal of the advertisement.

3. Universals can therefore be found in the emotional response of homogeneous cultural groups to advertisement music.
4. This knowledge can be applied in a music technological context and thus be helpful in the assessment and composition of functional advertisement music.

The research endeavour consists of two main aspects: Firstly a qualitive theoretical review in the form of a comprehensive literary study. Due to the abstract nature of the variables being measured, e.g. *affection*, *use of emotion* in advertisement music, the *influencing* of individuals, *personal differences* in perception, most constructs will be observed indirectly. This will be done by focusing on various empirical studies conducted in the past decades in the fields of Psychology of Music, Cognitive Psychology, Music Therapy, Neuropsychology, Cognitive Science, Cognitive Systematical Musicology, Consumer Science and Artificial Intelligence. Results from the above-mentioned studies, which have already been proven as valid and reliable, will be used as units of analysis.

The second part of the intended study will be to establish the feasibility of applying results from the theoretical review to a musical technological context. The possibility of creating a computer-based resource tool -which could serve as an aid to people working in the advertising industry- will be examined. As previously mentioned, the tool considered is an artificial neural network applied to a framework of musical pattern recognition. If the results of the explorative study show the hypotheses to be true, this knowledge will be used to create a neural network model, which can be used in a future study to assess functional advertisement music.

In conclusion, it must be made clear that the scope of the thesis does not provide for the actual implementation of the above-mentioned concept. The practicability and feasibility of the conceptual idea will only be examined, with the assumption that, if the idea is workable, it can be implemented in a future study.

The outline of the thesis is as follows. Chapter 1 provides an introduction to the subject of emotion and its relationship with music. Following this section, the main theoretical perspectives that collectively constitute a framework and paradigm for the study will be discussed, with a focus on

Cognitive Systematic Musicology, which constitutes the main paradigm. Chapter 2 serves as an introduction to the application part of the research project and discusses artificial neural networks and its applicability to the study. Chapter 3 discusses artificial neural networks as employed in the domain of music, and elaborates on musical network architectures. Chapter 4 serves as the theoretical foundation of the musical network model, presented in Chapter 5, and discusses a few methodological considerations in relation to the employment of an artificial neural network in a predominantly social scientific situation. To conclude, Chapter 5 provides an amalgamation of the ideas and issues offered in all of the former sections, in presenting a musical network model for usage in advertisement music research.

References

Huron, D. (1989). Music in advertising: An analytic paradigm. ***The Musical Quarterly***, (73/1), 557-574.

Woodward, W. (1982). ***An insider's guide to advertising music.*** New York: Art Direction Book Company.

Zaknich, A. & Baker, S. K. (1998) A real-time system for the characterisation of sheep feeding phases from acoustic signals of jaw sounds. ***Australian Journal of Intelligent Information Processing Systems,*** (5/2), Retrieved February 2004 from the World Wide Web: ftp://ftp.sas.com/pub/neural/FAQ7.html

CHAPTER 1: THEORETICAL FRAMEWORK

The thesis approaches the research problem from a multidisciplinary perspective. For this reason, the theoretical premises of respectively the Psychology– and Social Psychology of Music, as well as the various fields incorporated in Cognitive Science, will be taken as points of departure. Conceptualised as a subdiscipline of Cognitive Science, Cognitive Systematic Musicology will be accepted as the main paradigm.

1.1 INTRODUCTION TO THEORETICAL PERSPECTIVES

Over the past centuries, the broad theme of the emotional effect of music on individuals had been considered from within diverse fields with accompanied distinctive paradigms. The scope of this research endeavour doesn't allow an all-inclusive description of this topic. The following assemblage of contributions by various authors, including Juslin & Slobada (2001), Grout & Palisca (1996), Aristotle (1998), Randel (1986), Baker (2001), Giomo (1993), Paddison (2001), Meyer (1956), Cooke (1990) and Adorno (1997), attempts to provide an overview consisting of the most significant historical contributors in this regard.

In Greek mythology, music had a celestial origin. Its creators and practitioners were perceived as gods or half-gods. Music was ascribed certain supernatural abilities, such as healing illness, purification of the body and mind and conducting miracles in nature. Greek music theorists, following after Pythagoras [c. 582-500 B.C.], formulated principles on the philosophy and science of music that have survived to this day (Grout & Palisca, 1996: 4).

These early Greek scholars expressed musical thought in two divisions of theoretical writings. The first focussed on the character of music, its place in the universe, the effects thereof and its appropriate uses in society. The other part systematically described the components and patterns of composition. Scholars of the first viewpoint believed that music possessed ethical qualities and could affect human character and behaviour. The soul was seen as a composite which was kept in harmony by numerical relationships – an idea in fitting with the Pythagorean view of music as a system of pitch and rhythm ruled by the same mathematical laws that function in the visible and invisible world.

Aristotle [384-322 B.C.] was of opinion that music has great influence on the human soul and behaviour (1998: 227-242).[1] In his *theory of imitation*[2] he states that music represents the *passions* (conditions) of the soul - such as gentleness, anger, courage, temperance as well as the opposite of these attributes:

> *It is evident that melodies themselves contain representations of the components of character. For, in the first place, harmonies have divergent natures, so that listeners are affected differently and do not respond in the same way to each one. They respond to some (for example, the so-called Mixo-Lydian) in a more mournful and solemn way; to others their response is more tender-minded; their response to the Dorian is particularly balanced and composed, whereas the Phrygian causes them to be inspired…The same also holds of the different rhythms. Some have a steadying character, others get us moving; and some of these movements are more slavish or boorish, whereas others are more free (Aristotle, 1998: 236).*

He also claims that music which imitates or represents a certain feeling arouses that feeling in the listener; thus repeated exposure to the right or wrong kind of music could correspondingly enhance or distort a person's character.

In the 16th century, music theorists like Zarlino [1517-1590] again took up the notion that music should arouse human moods. This viewpoint was in accordance with the aims of what classical writers defined as the paradigm of *rhetoric* (Randel, 1986:16). Later on, in the 17th and 18th centuries, scholars of music believed that the principal aim of music was to arouse the human affections like joy, love, fear, anger and hate. In this *doctrine of affections* it was thought that music could mimic the animate and inanimate world, the nuances of speech and the emotions. The imitation was accomplished by the *rhetoric method*, with its intention to arouse the listener (Baker, 2001:463). In this regard the reader is referred to Dubos's [1670-1742 B.C.] *Réflexions critiques sur la poésie et sur la peinture*[3] (1740), who considered art as a means of provoking moderate passions in persons. In music, this could be achieved by literally impersonating nature such as tone-painting, or by a higher category reflecting the inner state or feelings of people. The doctrine of affections also included the view that a section of music or composition as a whole should have a unity of affection.

It is clear that these philosophers, even in ancient times, acknowledged and appreciated the fact that music could command significant power over the human mind and emotion. Consequently, they have

---

[1] Aristotle's *Politics* was originally published in ca. 330 B.C.

[2] The *theory of imitation* is cited from *Politics* and also discussed in Grout & Palisca (1996: 6).

[3] Critical reflections on poetry, painting and music.

also been struggling with the problem of formally and academically defining the relationship between *music*, *emotional expression* and *affective meaning* for the last 26 centuries, resulting in the surfacing of three basic positions as described by Giomo (1993:142). The first, supported by Plato's *Republic* (1928), holds that mood states are embodied within a musical work and capable of affecting the character of the listener. Tolstoy (1979), among others, supported the second viewpoint in his assumption that the composer communicates his/her unique emotional state through music – music becomes a second language. Meyer (1973), who stated that the listener him/herself imposes affective meaning to musical forms based on cultural conditioning and experience, defined the third approach.

Paddison (2001:465) states that – in spite of the *anti-expression aesthetic* of the 20th century as a counter-reaction to the Expressionist movement – the perception that music is about the expression of emotion maintained a strong influence on the music-loving public and still presents an important theme for musical and philosophical aesthetics. In this regard, the writings of Meyer (1956), Cooke (1990) and Adorno (1997) represent contrasting views on the way in which the theory of musical expression continued to be dealt with from the 1950s.

Meyer presented a psychological theory of musical expression based on the notion of degrees of tonal tension and relief. He suggested that expression is the result of disruptions in the goal-orientated inclinations of a musical impulse against an environment of stylistic and syntactic probability. In *The Language of Music*, Cooke (1990)[4] argued that it is achievable to create a lexicon of the expressive gestures of the vocabulary of music. He specified the array of elements of musical expression as a system of tonal tensions, which can be understood melodically as well as harmonically. He also claimed that there exists a natural association between musical figures and feeling, and that these musical gestures are legitimate for all time, liberated from any social and historical context. Adorno's view contradicted those of Meyer and Cooke, saying that the enigmatic character of independent musical works is the result of the antagonism between the logic and rationality of musical structures and the seeming irrationality of expression.

In addition to the previously described viewpoints, music psychologists have also been systematically studying the correlation between music and human moods for at least the last hundred years. For the greater part of the 1900s, research had been focused on the construction of lists of adjectives to identify the affective states in musical examples. Prominent studies of this nature included those of Hevner (1936) and Farnsworth (1954). More recent studies, aimed at the identification of affective states in

[4] *The Language of Music* was first published in 1959.

relation to music, incorporated alternative research methods like semantic differentiation and the correlation of musical mood with colours, visual forms, dance movements and finger-tip pressure (Giomo, 1993).

The 1970s saw the realisation of a new and unique paradigm to study this phenomenon by incorporating computational models and the digital computer, namely Cognitive Systematic Musicology – partly evolving as a result of the cognitive revolution which marked the preceding years. This research endeavour will mainly absorb the thoughts and premises of this paradigm in dealing with the research question.

From the preceding outline it should be evident that scholars from various fields of study clearly acknowledged the existence of a certain connection between music and human emotion. Juslin & Slobada (2001) goes so far as to argue that a certain kind of emotional experience is perhaps the most important facet underlying most people's engagement with music, and that the emotional facets of music should be at the centre of a musical science. To conclude this succinct introduction, the following citation is extracted from Scruton (2001:466):

> *In every age it has been accepted that there is some relation between music and the passions – a relation, say, of instruction (Plato), of imitation (Aristotle), of arousal (Descartes, Mersenne), of "fusion" (Santayana) or simply of some mysterious 'correspondence' about which nothing further can be said (St Augustine). It was from a sense of the emotional power of music that the Greek philosophers debated its political significance, that the Council of Trent considered how to subdue its influence in the liturgy, and that Calvin warned against its appeal in his preface to the Geneva Psalter. Yet the relation between music and emotion has remained obscure, and even when, partly under the influence of Rousseau and Diderot, the term "expression" began to be preferred as the proper name for this relation, philosophers remained baffled as to its detailed character.*

As stated, this dissertation takes a multidisciplinary approach to the research problem. Therefore, the theoretical principles of respectively the Psychology of Music, Social Psychology of Music, Cognitive Science and Cognitive Psychology will be reviewed in the next section. Cognitive Systematic Musicology will be discussed as a separate entity in 1.3.

1.2 THEORETICAL PERSPECTIVES

1.2.1 Psychology of Music

Portrayed as a *subdiscipline of systematic Musicology* in the *New Harvard Dictionary of Music* (Randel, 1986: 521), Psychology of Music studies individual human musical thought and behaviour from a scientific perspective. The origin of this field can be traced back as far as the 6th century B.C., with the first reported research done in the experimental method ascribed to Pythagoras. Following Pythagoras, scholars turned their attention away from the experimental method and tried to explain musical phenomena in terms of mathematical relationships instead. However, it was Aristoxenus [445 –345 B.C.] who prognosticated the modern study of the Psychology of Music. He stated that music could not be explained in terms of mathematical relationships alone – musical phenomena are characteristically perceptual and cognitive and should be studied as an experimental science (Deutsch, 2001:527).

Following these early roots, Psychology of Music developed more or less along the lines of mainstream Psychology – influenced, amongst others, by Empiricism, Structuralism, Gestalt Psychology, and the school of Behaviourism. Since the 1960s the most important influence in the field has been Cognitive Psychology, with the computational metaphor featuring as its main theoretical instrument. Cognitive Psychology and its theoretical contributions of value to this study will be discussed in section 1.2.4.

Music Psychology of the late 20th century focussed on four main topics. Slobada (2001:530) describes these as:

- *the cognitive representation of pitch and rhythm;*
- *the development of musical competence and skill;*
- *processes underlying musical performance;*
- *the affective processes associated with music listening, e.g. preference and emotion.*

Music psychologists have made some valuable theoretical contributions concerning the understanding of the affective processes subjacent to musical experience - which is of specific relevance to the study at hand. The main categories of *affect* are considered as *feelings, emotions* and *moods* (Slobada, 2001:544). Eysenck & Keane (2000: 489) offer a more comprehensive definition of the terms involved. They define *affect* as a very broad term that has been used to cover an extensive variety of experiences such as emotions, moods and preferences. *Emotion* refers to brief but intensive experiences, and a *mood* or *state* is described as a low-intensity but more prolonged experience.

Scholars of Music Psychology examine the question of why people report strong emotional reactions to music and by what means music creates affect. They state that music seems to elicit strong emotion more frequently and reliably than other art forms, and offer the following reasons (Slobada, 2001:544):-

- *Music happens over time and so is capable of engaging the emotions of expectation and expectations realized more effectively than static forms such as painting; drama, dance, film and literature share this feature with music.*
- *Music uses directly, and often mimics, the most emotionally important signal of the human species namely the voice.*
- *Music engages the auditory sense, which gives it a general arousing capacity due to the fact that we cannot escape the source of stimulation, as well as providing a link to the most primitive and fundamental feelings and experiences of human life.*

Similar to the method of mainstream Psychology, music psychologists distinguish between *extrinsic*- and *intrinsic* affect, but in relation to music. When musical stimuli is associated[5] with specific events or contexts from earlier life experiences and serve to trigger the recall of these events, one talks of extrinsic affect. Extrinsic affect seems to manifest itself best when the events are occasions of strong emotion. Amongst other, studies by Gabrielsson (1991) and Slobada (1991) have provided proof that specific pieces of music can activate strong emotion and lead the attention away from the present music to the remembered past context. These feelings are unavoidably linked to life experiences of the person involved and therefore highly idiosyncratic. Nevertheless, common cultural experiences can also lead to shared, extrinsic affect. Slobada (2001:545) gives some examples of these shared feelings, such as the *negative emotion* many Jewish people felt after the war on hearing the music of Richard Wagner; the powerful *emotional identification of generational cohorts with the popular music prevalent in their teenage years* and the *cultural associations created by film-music pairings*.

Intrinsic affect is described in relation to *iconic*- and *symbolical* associations between musical structures and emotional responses. An iconic relationship is manifested through a formal resemblance between a musical structure and an 'emotion-laden' agent. An example of this type of association is loud, fast music – which shares attributes with high-energy events – suggesting a high-energy emotion like excitement. A number of libraries of these iconic relationships are in existence, for example those developed by Hevner (1936) and Wedin (1972). When a listener's response is established through an appreciation of formal and syntactic properties of a musical phrase, a symbolic association is manifested. Musical sequences can bring about anticipation in listeners. These expectancies can be based on the basic characteristics of human perception or on familiarity with musical styles and genres. Regularly working on a subconscious level, confirmations or violations of expectancies can establish emotional responses to music. Seeing that the manifestation of both extrinsic- and intrinsic affect

[5] In the human memory system.

frequently depend upon existing knowledge (biographical or related to specific musical styles), cultural and developmental factors will influence emotional responses.

To conclude this review, it is imperative to discuss a few shortcomings of the traditional paradigm of Music Psychology, partly for the reason that Cognitive Systematic Musicology aims to address some of these issues. As part of *The 1999 Ernest Bloch Lectures,* held at the Department of Music, University of California, Berkeley, Huron (1999:2) stipulated four problems that have, in his own words, *haunted music Psychology* over the past years:

Music Psychology has placed the individual and individual reactions to music at the center of their attention with negligence towards social and cultural contexts. Secondly, the discipline concentrated on low-level problems of sensation and perception with modest significant consequences to musical experience. In this regard, Huron states that *To this day, most books on the Psychology of Music typically include lengthy discussions of acoustics and psychophysics without showing how these matters might relate to the quality of musical experience.* The third limitation is that research conducted, which involved more musically appealing issues, has been predisposed to accentuate the limitations of music listening. According to Huron, a creative or imaginative constituent has so far been absent in Music Psychology. The field has not commenced investigations into innovative and unexplored musical environments. The last issue relates to researchers who previously directed the field with their *conservative musical tastes,* and accordingly have paid little attention to contemporary music nor attracted scholars accessible to new music.

In addition to these, Juslin & Slobada (2001) present a few possible explanations for the slow progress in the study of music and emotion. Firstly, they claim that for obvious reasons – similar to the study of emotion in general in other fields – it is problematical to examine emotion by means of laboratory experiments. Emotion in music is a difficult subject and many scholars are hesitant to scrutinize it. Secondly, the dominant influence of Cognitive Science on the field of Psychology and Psychology of Music[6] has lead to an emphasis on cognitive features of musical behaviour – found on a unified *information-processing*[7] paradigm. Consequently, the emotional aspects underlying music has been greatly neglected. Finally, they argue that the academic study of music is paradigmatically largely dependent on a very specific method of listening to music and talking about it …*that is enshrined in the narrow "classical concert culture" where audiences are taught to listen 'silently and respectfully' with minimum bodily movement or emotional expression. "Appreciation" of music is often taken to mean having an intellectual understanding of the history and form of*

[6] Refer to Gardner (1983) in this regard.

[7] Refer to 1.2.4.

the musical composition, rather than an articulated emotional response. …As a consequence, there have been few academic discourses available in which to frame and articulate a relevant understanding of the emotions. Juslin & Slobada (2001:5)

1.2.2 Social Psychology of Music

Scholars in the field of the Social Psychology of Music, a more recent branch of Music Psychology, have made some considerable contributions in taking a cultural and societal view of Music Psychology. These theoretical contributions are of the utmost importance to the study, and cannot be overlooked in this regard.

From a physics point of view, music is the organization and configuration of particular frequencies, amplitudes and timbres. However, these sounds only acquire significance in a certain *social* and *cultural* context (Hargreaves & North, 1997:1). Consequently, social music psychologists perceive music as a fundamental social and culturally related activity.

The social and technological changes of the past decades caused music to attain new purposes in everyday life. The development of the mass media, telecommunications and technological advances in music creation-, storage-, transferring- and listening devices, have expanded the usage of music of both ordinary people and musicians. Historical boundaries that existed between different musical styles and genres are narrowing down, while the applications of music are increasing. Examples of relatively new functions of music include its usage in educational- and therapeutic applications; the creation of relevant ambience in commercial settings or increased work performance in industries; and most importantly for the scope of this thesis establishing a brand image in advertising. Social music psychologists analyze this interaction between musical behaviour and the social environment on three levels, relating to *individual differences*, *social groups and situations* and *cultural influences* (Hargreaves, Kemp & North, 2001:558).

The study of individual differences in musical behaviour and the ways in which these are influenced by the social environment are mainly focused on age, gender and personality factors. Relating to social groups and situations, social psychologists have found that people's judgments frequently conform to those of a social group. Applied to music, this means that some individuals will choose to listen to music that they dislike if they believe that a significant external group does like it. The social environment may also influence responses to music by affecting the autonomic nervous system. Individuals habitually seem to prefer music that tone down acute levels of environmentally induced arousal, for example after exercising or being insulted (which both induce high arousal), people tend to favour comforting music. Lastly, musical behaviour is also influenced by the broader culture in which it is composed and listened to. In recent years, psychologists have begun to use computerized analyses to examine historical and cultural trends in musical behaviour. All of the above-mentioned factors will be discussed in detail in the literary review and made applicable to the field of advertising music.

Up to now, the discussion on theoretical perspectives has been founded solely on a human- or social scientific paradigm. The following sections are predominantly based on the natural sciences and include Cognitive Science, Cognitive Psychology, and Cognitive Systematic Musicology.

1.2.3 Cognitive Science

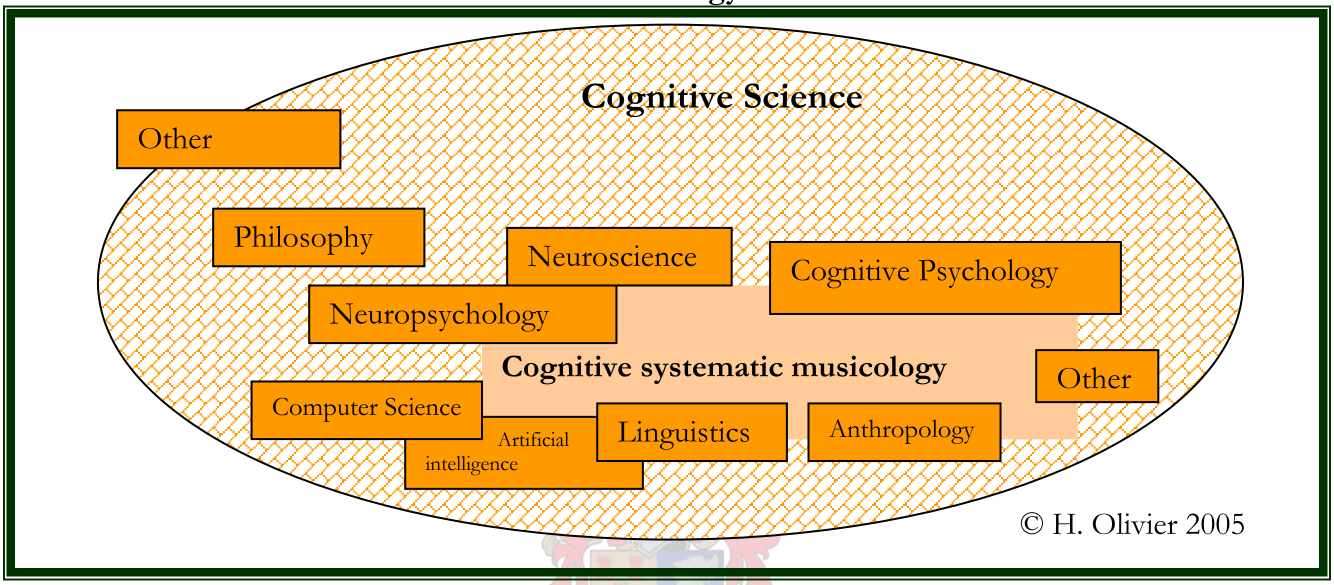
One of the most significant and influential scientific developments in recent years has been the emergence of the field of Cognitive Science - a unifying, all-encompassing paradigm aimed at describing and understanding the human mind. Also defined by Posner as *the study of intelligence and intelligent systems, with particular reference to intelligent behavior as computation* (1989:1), this author states that it is unexceptional nowadays to attribute intelligence to human as well as inhuman systems such as programmed computers. In this regard, a program will be labeled as intelligent if it demonstrates behaviour that would otherwise be regarded as intelligent when performed by a human. Posner is of the opinion that intelligence should be judged by the capability to perform intellectual tasks, independent of the nature of the concerned physical system.

Cognitive Science is a transdisciplinary grouping of a number of study fields with a shared main goal of describing human cognition. These include Philosophy, Experimental Psychology; Cognitive Psychology, Social Psychology; Neuroscience, Neuropsychology, Artificial Intelligence (within Computer Science), Linguistics, and Cognitive Anthropology (Posner, 1989; Von Eckardt, 1993; Eysenck & Keane, 2000). Most importantly, for the purpose of this study, Cognitive Systematic Musicology will also be classified as belonging to this group. Figure 1.1 illustrates the relation between Cognitive Science, Cognitive Psychology, and Cognitive Systematic Musicology.

The field of Cognitive Science does not formally acknowledge musical cognition as an area of research. In spite of this, the following citation from Cross & Deliège (1993:1) supports a cognitive scientific approach applied to the context of music:-

…Cognitive science has increasingly come to be seen as offering an appropriate framework within to explore and to explain issues in musical listening, performance, composition, development and analysis. As Cognitive Science develops, it provides more and more sophisticated and plausible accounts of the phenomena of mental life. To approach music by means of Cognitive Science involves the scientific study of all aspects of the musical mind and musical behaviour at all possible levels of explanation – be it neurophysiological, psychoacoustical or cognitive psychological. This is conducted by theoretical or empirical inquiry and by means of computer modelling or by practical experiment.

Figure 1.1 A view on the connection between Cognitive Science and Cognitive Systematic Musicology



The year 1956 proved to be a very significant and decisive year in the development of both Cognitive Science and Cognitive Psychology as major disciplines. At a meeting at the Massachusetts Institute of Technology, Chomsky presented a paper on his theory of language, Miller gave a presentation on the *magic number seven* in short-term memory, and Newell & Simon discussed their computational model called the *General Problem Solver* (Eysenck & Keane, 2000:1). The first methodological attempt considering concept formation from a cognitive perspective was also reported. In addition to these, the field of Artificial Intelligence was founded in the same year at the *Dartmouth Summer Research Project on Artificial Intelligence*[8], which was attended by all of the above-mentioned individuals. It was at this same conference that the subdiscipline of neural networks was officially launched and brought to national attention (Smith, 1999:12).

Cognitive Science strives to represent theoretical assumptions and hypotheses in computational models, which in turn can be represented by computer programs. These programs are expected to produce the same outputs as people when given the same inputs. One of the major benefits of the computational

[8] Organized by Marvin Minsky, John McCarthy, Nathaniel Rochester, and Claude Shannon.

models developed in Cognitive Science is that these can provide both an explanatory and predictive basis for a phenomenon. The main types of computational models that have been used in recent years are semantic networks, production systems and connectionist networks (artificial neural networks). The latter will be focused upon in the application of the thesis, and the relevance thereof explained with more detail in chapter 2.

Amongst others, the field of Cognitive Science resulted in the establishment, development and progress of various other disciplines such as Cognitive Psychology.

1.2.4 Cognitive Psychology

Cognitive Psychology focuses on a range of diverse phenomena in the realm of human cognition, unified by the basic assumption that there is a marked similarity between the human mind and the digital computer: *the information-processing approach*. Various other disciplines, including the field concerned with consumer behaviour, also employ this approach as dominant paradigm (Bettman: 1979, also cited in Mouthino et al., 1994). From within this theoretical perspective, the mind is seen as a general-purpose, symbol-processing system with a limited capacity. By the end of the 1970s, most cognitive psychologists agreed that the information-processing framework was the best way to study human cognition. This framework is fundamentally defined by seven main points (Eysenck & Keane, 2000:2), although it is continuously developing in accordance with the expansion of information technology:-

- *People are autonomous, intentional beings interacting with the external world.*
- *The mind through which they interact with the world is a general-purpose, symbol-processing system.*
- *Symbols are acted on by processes that transform them into other symbols that ultimately relate to things in the external world.*
- *The aim of psychological research is to specify the symbolic processes and representations underlying performance on all cognitive tasks.*
- *Cognitive processes take time, and predictions about time can often be made.*
- *The mind is a limited-capacity processor having structural and resource limitations.*
- *The symbol system depends on a neurological substrate, but is not wholly constrained by it.*

Cognitive psychologists differentiate between bottom-up- (stimulus-driven) and top-down (conceptually-driven) cognitive processing, and claim that most cognitive activity consists of these processes interactively happening together. Stimulus-driven processing is directly affected by a stimulus input while conceptually-driven processing is influenced by contributes of the individual, like expectations caused by the context of the situation and past experiences.

As stated, the information-processing paradigm is constantly evolving on par with information technology – the computational metaphor is continually being extended as computer technology develops. Researchers in the 1950s and 1960s – in their attempts to understand the human mind – mainly focussed on the general properties of the computer like its central processor and memory registers. By the 1970s, many programming languages had been developed, leading to the usage of computer software and -languages. After that, with the realisation of parallel-processing models, theorists returned to the belief that cognitive theories should be based on the parallel processing abilities of the brain (Eysenck & Keane, 2000:3).

Theories and methods from twelve main areas of research shape the contemporary field of Cognitive Psychology (Solso, 1991:6). These subjects encompass developmental Cognitive Psychology, Brain Science, human intelligence, Artificial Intelligence, perception, pattern recognition, attention, memory, imagery, thinking and problem solving, representation of knowledge, and language functions.

The *academically* acknowledged field of Cognitive Psychology as described in the previous paragraph does not concentrate per se on music as a primary subject of interest in its paradigm. It rather focuses on more general aspects of human perception and -behaviour that can be inferred to have relevance to music. In contrast to this point of departure, from a musical orientated perspective, there is a great deal of interest towards Cognitive Psychology.

Some scholars of music believe that there is much to gain from the research conducted in-, and theoretical premises of Cognitive Psychology. This confidence manifests to such an extent that Dufourt (1989) even mentions a subject called C*ognitive Music Psychology* in an article titled *Music and Cognitive Psychology: Form-bearing elements*. The main goal of this article is to emphasise the interdependence of music and Cognitive Psychology. Dufourt claims that the relationship of Cognitive Psychology to contemporary music is that of a theory to its models: Cognitive Psychology specifies a theory of the relations between memory and perception for which music can serve as a test of effectiveness and coherence.

Similar to the information-processing paradigm of Cognitive Psychology, Cognitive Systematic Musicology studies musical thought by using a computational model that aims to explain the process of musical cognition in *computational terms* (Kugel, 1990:12). As mentioned previously, Cognitive Systematic Musicology is accepted as the main theoretical paradigm of this dissertation. Consequently, the theoretical assumptions, perspectives and epistemologies underlying this field will be discussed in detail in the next section.

1.3 COGNITIVE SYSTEMATIC MUSICOLOGY

1.3.1 Introduction to Cognitive Systematic Musicology

Cognitive Systematic Musicology is acknowledged as one of the youngest of the Cognitive Sciences.[9] This field of study only established itself as a paradigm of full value in the 1970s, resulting from prominent theoretical contributions made by Laske. Following this groundwork, some later contributions were made by – amongst others – Dufourt (1989), Kugel (1990), Cross & Deliège (1993), Leman (1995) and Hörnel & Menzel (1998). It developed from a range of diverse fields, e.g. Musicology, Cognitive Psychology, Neuroscience, Artificial Intelligence, Information Science, Philosophy, Anthropology, Linguistics, Speech Recognition, Semiotics and Psychoacoustics.

Laske (1988:43-55) defined *Cognitive Musicology* as the study of musical thinking from a computational point of view, which – like Cognitive Science of which it forms part – tends to focus on processes of musical thinking, rather than on products. Similar to Cognitive Science, these processes are characterized in computational terms. Huron (1999:28) provides another description of the field:

> *Cognitive Musicology is the study of habits of minds as they relate to music. Since minds are the products of both biology and culture, cognitive Musicology is an approach to the study of music that takes both biology and culture seriously. A common ground for both biological and cultural study is found in the domain of mental representations. Consequently, much of the day-to-day research of cognitive musicologists centres on discovering and deciphering various music-relates mental representations.*

Leman (n.d.) holds the opinion that this type of Musicology is the appropriate candidate to contribute actively to musical life in a modern information-technological society.

The main objective of Cognitive Systematic Musicology is the study of musical behaviour and – cognition in its many forms by way of computational representation. The field sees *musical intelligence* as an autonomous entity, independent and distinguishable from other human intelligences. This notion is in contrast to the traditional view of musical intelligence as a derivative of linguistical- or logico-mathematical competence. Even so, the belief of an independent musical intelligence is in agreement with the arguments of the psychologist and theorist Gardner (1983 &1993a), who proposed a theory of multiple intelligences based loosely on the study of brain-behaviour relationships. He argued for the existence of several relatively independent human intelligences and outlined the criteria for an autonomous intelligence as follows (Gardner, 1993a: 62 - 66):-

- *Potential isolation by brain damage – the faculty can be destroyed, or spared in isolation, by brain injury.*

[9] The reader is referred to Balaban, Ebcioğlu & Laske, (1992:4) & Laske, (1989:43) in this regard.

- *The existence of exceptional individuals such as savants – the faculty is uniquely spared in the midst of general intellectual mediocrity.*
- *An identifiable core operation or set of operations – the faculty relies upon one ore more basic information-processing operations.*
- *A distinctive developmental history – the faculty possesses an identifiable developmental history, perhaps including critical periods and milestones.*
- *An evolutionary history and plausibility – admittedly speculative, a faculty should have evolutionary antecedents shared with other organisms (e.g. primate social organisation).*
- *Support from experimental psychological tasks – the faculty emerges in laboratory studies in Cognitive Psychology .*
- *Support from psychometric findings – the faculty reveals itself in measurement studies and is susceptible to psychometric measurement.*
- *Susceptible for encoding in a symbol system – the faculty can be communicated via symbols including (but not limited to) language, picturing, and mathematics.*

Based on these criteria, Gardner proposed six natural intelligences – musical intelligence being one, which can be studied as a cognitive system in its own right. He defines the main components of musical intelligence as pitch (melody), rhythm (sounds emitted at certain auditory frequencies and grouped according to a prescribed system) and timbre (the characteristic qualities of a tone). These primary faculties are crucial to all participation in the musical encounters of a culture, and should be found in all normal individuals brought into recurrent contact with any kind of music.

According to Gregory (1996), musical intelligence is perhaps the least understood of Gardner's intelligences. Gregory states that persons with good musical intelligence can easily learn to perform on an instrument or to write their own compositions. Gardner (1993b:105) was of the opinion that – although knowledge of the *structural aspects* of melody, rhythm, and timbre are important to musical intelligence – many experts such as the composers Roger Sessions and Arnold Schoenberg placed the *affective* or *emotional* aspects of music at its core. On this behalf, Gardner quoted the following statement of the composer Arnold Schoenberg (1965:186):

> *Music is a succession of tones and tone combinations so organized as to have an agreeable impression on the ear and its impression on the intelligence is comprehensible…These impressions have the power to influence occult parts of our soul and of our sentimental spheres and...this influence makes us live in a dreamland of fulfilled desires or in a dreamed hell.*

In closing, Gardner also believed that when the neurological underpinnings of music are finally unravelled, we will have an explanation of how emotional and motivational factors are intertwined with purely perceptual ones.

1.3.2 Historical development

A question that can be posed at this point is why a cognitive approach to music is such a recent phenomenon. It seems to be the perfect solution to researching an otherwise very subjective field. Traditionally, the study of music was approached from the paradigm of *Musicology,* a term that has been defined in many ways. The *New Grove Dictionary of Music and Musicians* defines Musicology as *the scholarly study of music…as a method, it is a form of scholarship characterized by the procedures of research* (Duckles & Pasler, 2001:488).

According to Cook & Dibben (2001:45), the English term was only used from the 20th century (being borrowed from the earlier employed French term *musicologie).* These authors argue that the appearance of Musicology can be ascribed to a novel relationship between compositional theory and practise, and a greater systemisation of the human sciences in the 19th century. They define the term, from a British perspective, as …*the study of and knowledge about all aspects of music, taking in, for example, the systematic approaches to musical organization collectively known as 'music theory'.* In addition to this definition, they claim that the American usage of the term, as described by Kerman (1985:11) is more limited: …*the study of the history of Western music in the high-art tradition.*

Adler (1919:7) first claimed the distinction between *Historical* and *Systematical* Musicology, and charted their essence and method.[10] Cited very briefly, his outline of the *Historical field* encompassed the auxiliary sciences of *musical palaeography, basic historical categories, laws, and musical instruments.* He said that the systematic field encorporated the auxilary sciences of the *investigation and justification of these laws in harmony, rhythm, and melody; aesthetics and psychology of music; music education;* and *Musicology (*referring to the *investigation and comparitive study in ethnography and folklore).* Duckles & Pasler's entry in *The New Grove Dictionary of Music and Musicians* claims that *Systematic Musicology is not a mere extension of Musicology but a complete reorientation of the discipline to fundamental questions which are non-historical in nature. These include aesthetics and research into the nature and properties of music as an acoustical, physiological, psychological and cognitive phenomenon. A systematic approach can also be given to all of Adler's historical areas, such as, for example, a semiological approach to musical notations and typological classifications of musical forms research* (2001:488).

The New Harvard Dictionary of Music (Randel, 1986: 520) defines Musicology as …*the scholarly study of music, whether it is found historically or geographically. The methods of Musicology are any that prove fruitful with respect to the*

[10] Adler's tabulation of the *auxiliary sciences* of Musicology is also cited in *The New Grove Dictionary of Music and Musicians* (Duckles & Pasler, 2001: 490).

particular subject of study. Because Musicology has become steadily more diverse in both subject and method, certain traditional boundaries among its subdisciplines have been blurred. The subdisciplines and subjects of study identified are Ethnomusicology, Historical Musicology, Systematical Musicology (including theory, acoustics, aesthetics, pedagogy, Psychology- physiology- and Sociology of music), iconography and organology. This source mentions linguistics and some aspects of computer science as independent disciplines of increasing relevance to the study of music.

The traditional divisions of Musicology (historical- and systematical-) were to a degree limited to only theorizing about music, with the result that the Musicology of the past fell short of an applied part – a shortcoming that Cognitive Systematic Musicology definitely accounts for. For the past century, traditional Musicology has therefore been struggling to prove its field as scientifically valid, often with less success.

At this stage, it will be worth mentioning that scholars of Musicology have no agreement in defining the field. What becomes clear in the various definitions, though, is that the traditional school of Musicology shows very little interest in, nor offers much scope for the incorporation of Cognitive Systematic Musicology as an acknowledged subdiscipline of their field of study. They never even mention this field as being a component of Musicology. A confirmation of this statement can be inferred from Duckles & Pasler (2001:491) entry in *The New Grove Dictionary of Music and Musicians*. This author discusses some new trends in Musicology – for example a focus on Musicology as a form of criticism, resembling the humanistic disciplines, and borrowing from literary or cultural theory and gender studies. Other modern viewpoints discussed include those of scholars who question the basic assumptions of historical Musicology; those influenced by *structuralist anthropologists*, *semioticians* and *sociologists*; as well as scholars following *postmodernist* notions. Nowhere in this article is a cognitive systematic approach included, or any mention made about a computative approach to Musicology.

In *Music, Gestalt and Computing,* Leman (1997:30) discusses the *unbalanced* relationship between systematic, historical and cognitive Musicology. He argues the case for collaboration in these fields and states that Cognitive Systematic Musicology may broaden the research field of systematic Musicology. To quote the author: *Cognitive Musicology, especially simulations with artificial neural networks, may give new possibilities to apply systematic methods in the study of some aspects of the history of music.*

Advances in the fields of the Cognitive Sciences, applied Artificial Intelligence, as well as developments in computer technologies and musical software engineering, made it imperative to broaden the notion of Musicology, extending its paradigm in order not to stagnate in a modern technological- and information science-driven world. Laske (1989:20) supports this statement: …*a combination of Cognitive Science and Artificial Intelligence challenges all aspects of classical theorising of music.*

In a modern context, many areas of music exist in a very close association with the digital computer. A few examples are the use of musically related computer-hardware and -software in educational settings, business organisations, concert halls, recording studios, as well as the private usage thereof and within the whole of the commercial music industry. This can mainly be attributed to extensive progression within the broad domain of computer science and –technology. These technological developments also contributed towards the realisation of 'music technology' as a new subject within the paradigm of Musicology, which aims, amongst others, to examine the relationship and association between music and the computer.

According to Cross & Deliège (1993) it is easily understood why music is such a new area of focus for cognitive scientists. Musical behaviour is internally transient and only during the past 30 years were adequate metaphors developed which can express the mental processes that can be inferred as underlying the observed musical behaviours. Furthermore, the technologies fundamental to the accurate and economical recording and examination of musical behaviour, developed to an adequate degree of sophistication at a very late stage.

Despite these advances in the means of enquiry, it was suggested until recently that attempts to understand music in cognitive terms were inadequate. Studies were condemned as being over-reductionistic and musically or psychologically simplistic. Fortunately, this situation changed with progressive and effective communication between musicians and cognitive scientists. As a result, research in the domain of the Cognitive Systematic Musicology has grown to a sophisticated level over the past 15 years; nowadays studies reflect an *awareness of* and *responsiveness* to *historical, analytical, practical* and *pedagogical* perspectives on music (Cross & Deliège, 1993:2). Laske (1989) rightfully states that the interdisciplinary character of traditional Musicology contributed to a lack of shared premises and methodologies that the Cognitive Systematic Musicology provided in its representation of musical knowledge in computational terms.

1.3.3 Research domain and limitations of Cognitive Systematic Musicology

Cognitive Systematic Musicology can be broadly divided into two fields of study. Firstly, a *theoretical* aspect which focuses on the formulation of hypotheses and problem-solving. Secondly, an *applied* field which aims to develop computer systems to intelligently assist musicians, as well as to test hypotheses constructed within the theoretical faculty (Laske, 1989:44). The author of this thesis is of opinion that research conducted in these two areas sufficiently addresses the problem of the scientific validity of Musicology, by providing an adequate medium (the digital computer) to formally and explicitly test and represent knowledge of musical thought.

According to Laske (1989), it has only recently become possible to bridge the traditional irreconcilability between the physical (natural sciences) and the mental (humanities), by approaching musical study from a computer scientific perspective. The rationale for his statement is that a computer is both a physical system and a symbol-processor. By its basic existence and functionality, it demonstrates the possibility of a physical, non-human system to conduct a cognitive action (e.g. by symbol manipulation). Here the analogy with human cognition is obvious. Today, researchers in the domain of music are consequently challenged to explain their findings in terms of objective methods, rules, limitations and related constructs.

As mentioned previously, in the past decade Cognitive Science has increasingly been regarded as an appropriate framework from which to study musical behaviour such as musical development, composition, analysis, auscultation and performance. Such a research paradigm offers some prominent advantages. Firstly, Cognitive Science provides progressively more sophisticated and plausible accounts of the phenomena of mental life. Secondly, it offers modes of enquiry that appears to be largely culturally-neutral. This can contribute to the ecological validation of research, particularly studies regarding the most musicological frameworks of understanding - which are traditionally seen as being highly ethnocentric and culturally-specific. In addition, a number of different dynamics are stimulating the phenomenon of the *computerization of music*, or the embodiment of aspects of music in computer soft- and hardware. This drive towards representing elements of music in computational terms is motivated by powerful aesthetic, educational and commercial imperatives (Cross & Deliège, 1993).

As a result, the application of Cognitive Science to music helps to bridge the traditional gap between the experiential texture (what it feels like) and the language that is used to describe and to teach it. To confirm the above-mentioned, the following statement from Cross & Deliège (1993:1) is cited:

> *...the development of a Cognitive Science of music help to span the disjunction that exists between the ways that music is experienced by listeners and by practising musicians and the rational framework that conventionally constitute music theory, i.e. that is used to describe and to define music. This development proceeds by seeking to provide accounts of music that are consonant with the concepts of computability and with empirically-derived evidence about musical perception, performance and creation.*

Similar to any scientific field of study, Cognitive Systematic Musicology has both strong and weak aspects in its domain of research. Although some shortages were identified in the preceding discussion of relevant research, Myhill's work offers the most comprehensive summary of its shortcomings.

According to Myhill (as cited in Kugel, 1990), most of the aspects of musical cognition can be described with scientific accuracy. He also claims, however, that there is a certain level of musical thought which cannot fully be depicted and characterized in terms of computation alone. This argument reflects back to those mentioned previously by Aristoxenus – one of the first Greek scholars of music- who suspected as early as 320 B.C. that music could not be understood by solely considering mathematical associations.[11]

Myhill identifies three levels of thought in musical cognition. On the first level problems can be solved effectively by means of a total computation, for example to establish whether or not a chord can be classified as consonant in traditional musical terms. On the second level, problems can only be solved constructively by means of a partial computational model. Problems are identified as being explainable by constructive means if they can be mastered by a process that computes the solution – if one exists – but does not necessarily tell us effectively when no solution exists. The third level of musical thought deals with problems that can only be solved prospectively by means of *uncomputations* – for example to identify a piece of music as *beautiful*. One conclusion from Myhill's work is that theorizing about the concept of musical cognition should not be restricted to computational models alone. On some levels, musical thought is flexible and inexhaustible – thus conceptional resources more powerful than computational models alone are needed to accurately describe musical cognition:

> *To say that we cannot fully characterize musical thinking in computational terms need not imply that we cannot fully characterize musical thinking in mechanical terms…. We will have to do it in terms of machines that are more powerful than computing machines ...we need trial-and-error machines to fully characterize musical thinking (Myhill in Kugel, 1990:13).*

A final restriction applicable to research within Cognitive Systematic Musicology is the practical implication of building knowledge-based systems to assist with music-related tasks. Because of the interdisciplinary character of the field, the task of transforming musical knowledge systems to practically applicable computer-software programs, is indeed a very difficult one. It has certain challenges and restrictions that falls outside the scope of this discussion – Laske (1989) provides a more comprehensive description in this regard. The afore-mentioned difficulties will however be adequately dealt with in the applied artificial neural network section of the thesis.

---

[11] Refer to section 1.1.

1.3.4 Contributions of Cognitive Systematic Musicology

Despite the limitations discussed in the previous section, Cognitive Systematic Musicology can contribute a great deal towards music research in general. Huron (1999:28-29) gives an account of these endowments related to various scholars involved in the discipline of music, including music historians and theorists, ethnomusicologists, performers and composers:-

- *For the historian, Cognitive Musicology offers the possibility of reconstructing aspects of seemingly lost practices. It also offers ways to approach how musical works and practices may have held meanings for listeners and musicians of past periods and places.*
- *For the music theorist, Cognitive Musicology promises to address basic questions of musical organization from a more rigorous and less speculative approach.*
- *For the ethnomusicologist, Cognitive Musicology offers relative effective techniques for gaining access to the minds of others, and useful ways of pinpointing how culturally sophisticated experiences differ from culturally naïve experiences. Cognitive Musicology also offers the ethnomusicologist better ways for investigating how material and cultural conditions get reflected and expressed in music.*
- *For the performer, Cognitive Musicology offers ways for investigating what distinguishes inexpressive and pedestrian performances from inspired and compelling ones.*
- *For the composer, Cognitive Musicology offers pointers to cognitively and perceptually rich regions of unexplored musical materials. In describing musical 'habits of mind', cognitive Musicology can help composers in their quests to establish new habits for the musical mind.*

In addition to these, Huron further believes that the increased appeal of music cognition over the past few years can be partly ascribed to the attraction that Cognitive Systematic Musicology has for academics from both an Anglo-American and Continental philosophical backgrounds:

> *For the continentally-inspired scholar, music cognition offers the opportunity to treat subjectivity as real without reifying it. Music cognition provides ways of considering the subjective without making it mystical or juxtaposing it irredeemably against the objective. Nor does it merely objectify the subjective. For the empiricist-inspired scholar, cognitive Musicology offers the opportunity to transform intuition and speculation into conjecture and hypothesis, and thereby provides a means for testing musical ideas and theories (Huron, 1999:29).*

1.3.5 Orientations in Cognitive Systematic Musicology

According to Leman (n.d:7), only Cognitive Systematic Musicology, which deals with music-related information processing, can offer an active contribution to musical life in the information society. An understanding of the associations between this branch of Musicology and information processing could reveal the contributions that this kind of musical research can make. These relationships can be specified along three main orientations, which collectively create a framework for this field.[12] The first is an *intuitive-speculative* orientation that concentrates on the accumulation of knowledge and the formulation of hypotheses. Its methodology is atypical from other empirical sciences in that it focuses on analysis, qualitative description and understanding rather than testing, quantitative description and prediction. The intuitive-speculative orientation is interested in the subject matter of traditional Systematic Musicology like musical practise, -theory, -analysis and semiotics, and draws on the tradition of Aristoxenos.[13]

The *empirical-experimental* approach is based on the disciplines of Psychoacoustics, Psychology of Music and Neuromusicology. In Psychoacoustics and Psychology of Music, information is usually obtained in laboratory conditions on a behavioural basis. Data are typically analysed statistically and associations between data and stimuli are inferred. Neuromusicology is concerned with human musical activities related to the brain, with its objective to accumulate knowledge into the neural encoding, localization of functions and dynamic principles that underlie human musical information processing (Leman: 1999). Neuromusicology gathers its information by the measurement of brain activity during human task performance. To observe sensory and cognitive functions, behavioural and physiological methods are often used in combination in its methodology.

The third orientation has a *computational- modelling* character and can be divided into a music-and-sound computational direction and the computational modelling of human musical information processing (perception and cognition). Music and sound computation focuses on features of musical signals like sound analysis, -synthesis and -transformation. The computational modelling of human musical information processing- category is concerned with the simulation of processes like perceptive-, sensory-, cognitive-, motoric-, and emotional responses. The objective of these simulations is to construct an operational theory which provides a foundation for testing and thus an understanding of the cognitive representations and dynamics underlying human musical behaviour (Leman, n.d:38).

Against this background, the thesis will constitute an overlapping of the three orientations in Cognitive Systematic Musicology. The literature review, presented in chapter 4, will be representative of the first two orientations. The application section, which will examine the possibility of creating a computer-based resource tool (artificial neural networks) to assist people working in the commercial music

---

[12] These orientations are also discussed in Leman (2003).

[13] Refer to section 1.2.1.

industry, will be approached from the computational-modelling realm. The following chapter will discuss artificial neural networks in detail and will serve as a vindication for the specific choice of this tool.

References

Adler, G. (1919). ***Methode der Musikgeschichte.*** Leipzig: Breitkopf.

Adorno, T.W. (1997). ***Ästhetische Theorie/ Aesthetic Theory.*** London: Athlone.

Aristotle, (1998). ***Politics*** (Translated, with introduction and Notes by C.D.C. Reeve). Indianapolis: Hackett Publishing Company.

Baker, N. K. (2001). History of the concept of expression: Before 1800. In Sadie, S. & Tyrrell, J. (Eds.). ***The New Grove Dictionary of Music and Musicians*** (2nd ed.), (8), 463-464.

Balaban, M., Ebcioğlu, K. & Laske, O. (Eds.). (1992). ***Understanding Music with AI: Perspectives on Music Cognition.*** Cambridge: The AAAI Press/ The MIT Press.

Bettman, J. R. (1979). ***An Information Processing Theory of Consumer Choice.*** Reading, Massachusetts: Addison-Wesley.

Cooke, D. (1990). ***The Language of Music.*** New York, USA: Oxford.

Cook, N. & Dibben, N. (2001). Musicological approaches to emotion. In Juslin, P. N. & Slobada, J. A. (Eds.). ***Music and Emotion,*** (45-70). Oxford: University Press.

Cross, I. & Deliège, I. (1993). Introduction: Cognitive science and music – an overview. ***Contemporary Music Review*** (9), 1-6.

Deutsch, D. J. (2001). Psychology of music: History. In Sadie, S. & Tyrrell, J. (Eds.). ***The New Grove Dictionary of Music and Musicians*** (2nd ed.), (20), 527.

Dubos, J. (1740). Réflexions critiques sur la poésie et sur la peinture /Critical reflections on poetry, painting and music. Chicago: University of Chicago Press.

Duckles, V. & Pasler, J. (2001). Musicology, l§: The nature of Musicology. 1. Definitions. 4. Historical and systematic musicology. In Sadie, S. & Tyrrell, J. (Eds.). ***The New Grove Dictionary of Music and Musicians*** (2nd ed.), (17), 488-490. London: Macmillan.

Duckles, V. & Pasler, J. (2001). Musicology, l§: The nature of Musicology. 5. New Trends. In Sadie, S. & Tyrrell, J. (Eds.). ***The New Grove Dictionary of Music and Musicians*** (2nd ed.), (17), 491.

Dufourt, H. (1989). Music and Cognitive Psychology: Form-bearing elements. ***Contemporary Music Review,*** (4), 231-236.

Eysenck, M.W. & Keane, M.T. (2000). ***Cognitive Psychology: A student's handbook*** (4th edition). Hove: Erlbaum.

Farnsworth, P.R. (1954). A study of the Hevner adjective list. ***Journal of Aesthetics and Art Criticism***, (13/1), 97-102.

Gabrielsson, A. (1991). Experiencing Music. ***Canadian Journal of Research in Music Education,*** (xxxiii), 21 –26.

Gardner, H. (1983). ***Frames of mind: The theory of multiple intelligence.*** New York: Basic Books.

Gardner, H. (1993a). ***Frames of mind: The theory of multiple intelligence: Tenth-Anniversary Edition.*** New York: Basic Books.

Gardner, H. (1993b). ***Multiple intelligences: The theory in practice.*** New York: Basic Books.

Giomo, C. (1993). An Experimental Study of Children's Sensitivity to Mood in music. ***Psychology of Music,*** (21/2), 141-162.

Gregory, R. J. (1996). ***Psychological Testing***. Boston: Allyn and Bacon.

Grout, D. J. & Palisca, C. V. (1996). ***A History of Western Music*** (5th ed.). New York: W.W. Norton & Company.

Hargreaves, D. J., Kemp, A. & North, A. C. (2001). Psychology of music: Social Psychology. In Sadie, S. & Tyrrell, J. (Eds.).***The New Grove Dictionary of Music and Musicians*** (2nd ed.), (20), 558-561.

Hargreaves, D. J. & North, A. C. (1997). ***The Social Psychology of Music.*** Oxford: Oxford University Press.

Hevner, K. (1936). Experimental studies of the elements of expression in music. ***American Journal of Psychology***, (48), 246-268.

Hörnel, D. & Menzel, W. (1998). Learning Musical Structure and Style with Neural Networks. ***Computer Music Journal,*** (22/4), 44-62.

Huron, D. (1999). ***The 1999 Ernest Bloch Lectures - Lecture 1. Music and Mind: Foundations of Cognitive Musicology.*** Retrieved November 6th, 2004 from the World Wide Web: http://www.music-cog.ohio-state.edu/Music220/Bloch.lectures/1.Preamble.html.

Juslin, P. N. & Slobada, J. A. (Eds.). (2001). ***Music and Emotion.*** Oxford: University Press.

Kerman, J. 1985:11 ***Contemplating Music.*** Cambridge, Massachusetts: The Harvard University Press.

Kugel, P. (1990). Myhill's Thesis: There's more than Computing in Musical Thinking. ***Computer Music Journal,*** (14/3), 12-25.

Laske, O. E. (1988). Introduction to cognitive Musicology. ***Computer Music Journal,*** (12/1), 43 – 57.

Laske, O. E. (1989). Introduction to cognitive Musicology. ***Musicological Research***, (12), 1-22.

Leman, M. (1995). ***Music and Schema Theory***. Berlin: Springer Verlag.

Leman, M. (Ed.) (1997). ***Music, Gestalt and computing***. Berlin: Springer.

Leman, M. (1999). Relevance of Cognitive Neuromusicology for music research. ***Journal of New Music Research,*** (28), 3.

Leman, M. (n.d). ***Systematic Musicology in the Information Society – Tendencies, Perspectives and Opportunities for Musical Content Processing.*** (Unpublished paper). Belgium: IPEM –Dept. of Musicology, Ghent University.

Leman, M. (2003). Foundations of Musicology as Content Processing Science. ***Journal of Music and Meaning,*** (1/1), 1-44.

Meyer, L. B. (1956). ***Emotion and Meaning in Music***. Chicago: University of Chicago Press.

Meyer, L. B. (1973). ***Explaining music.*** Berkeley: University of California Press.

Moutinho, L., Curry, B., Davies, F. & Rita, P. (1994). ***Computer Modelling and Expert Systems in Marketing.*** London: Routledge.

Paddison, M.H. (2001). History of the concept of expression: After 1800. In Sadie, S. & Tyrrell, J. (Eds.). ***The New Grove Dictionary of Music and Musicians*** (2nd ed.), (8), 464-466.

Plato, (1928). ***The Republic*** (Jowett, translation). New York: Charles Scribner's Sons.

Posner, M.I. (ed.). (1989). ***Foundations of Cognitive Science***. Cambridge, Mass: MIT Press.

Randel, D.M. (Ed.). (1986). ***The New Harvard Dictionary of Music.*** Cambridge: Harvard University Press.

Schoenberg, A. (1965). In Stein, E. (Ed.). ***Letters.*** New York: St. Martin's Press.

Scruton, R. (2001). The nature of musical expression. In Sadie, S. & Tyrrell, J. (Eds.). ***The New Grove Dictionary of Music and Musicians*** (2nd ed.), (8), 466.

Slobada, J.A. (1991). Music Structure and Emotional Response: some Empirical Findings. ***Psychology of Music,*** (xix), 110 –120.

Slobada, J.A. (2001). Psychology of music: Affect. In Sadie, S. & Tyrrell, J. (Eds.). ***The New Grove Dictionary of Music and Musicians*** (2nd ed.), (20), 530.

Smith, K.A. (1999). ***Introduction to Neural Networks and Data mining for Business applications.*** South Melbourne, Australia: Corporate Printers.

Solso, R.L. (1991). ***Cognitive Psychology*** (6th ed.). Boston: Allyn & Bacon.

Tolstoy, L. (1979). The communication of emotion. In Rader, M. (Ed.). ***A Modern book of esthetics*** (5th ed.). New York: Holt, Rinehart & Winston

Von Eckardt, B. (1993). ***What is Cognitive Science?*** Cambridge, Mass: MIT Press.

Wedin, L. (1972). A Multidimentional Study of Perceptual-Emotional Qualities in Music. ***Scandinavian Journal of Psychology ,*** (xiii), 241 – 257.

CHAPTER 2: NEURAL NETWORKS

As indicated in the introduction, the research endeavour focuses on two main aspects: a qualitative explorative theoretical review in the form of a comprehensive literary study, which will be dealt with in chapter 4. The other part of the study is to establish the feasibility of applying the outcome from the theoretical part to a musical technological context. This applied part is the main objective of the thesis - that the results concluded from the theoretical review could actually be constructively employed in the designing of a computer-based software tool aimed towards the assessment of cultural-specific, target-group orientated, goal-directed television advertising music. As previously revealed, the tool decided on is an artificial neural network applied to a framework of musical pattern recognition. This chapter will serve as a validation of the decision of artificial neural networks and accordingly an introduction to the applied part.

2.1 INTRODUCTION TO ARTIFICIAL NEURAL NETWORKS

Cognitive science aims to develop computational models in understanding human cognition. A sufficient computational model demonstrates that a given theory can be specified and enables the ability to predict behaviour. The field of Experimental Psychology employed mathematical models long before the emergence of the information-processing paradigm, but today's incorporation of computational models – developed in the Cognitive Sciences – has the benefits of providing both an explanatory and predictive basis for a phenomenon. The main types of computational models that are in use at present are *semantic networks, production systems* and *connectionist networks* (Eysenck & Keane, 2000:7).

Connectionist networks, parallel distributed processing models, or artificial neural networks, are relative newcomers to the computational modelling scene. According to Dolson (1991), physicists, mathematicians, electrical engineers, biologists, and cognitive scientists facilitated the development of the highly interdisciplinary field of neural networks. All of these scholars have depicted it in dissimilar terms, with the effect that *neural networks, connectionist models, parallel distributed models, massively parallel systems* and *artificial neural systems* all fundamentally relate to the same concept. In this document it will be referred to as artificial neural networks (ANNs).

Previous techniques were unified by both the needs to program explicitly all aspects of the model and to use explicit symbols to represent concepts. In contrast, an artificial neural network can to some extent program itself – by learning to produce specific outputs with certain given inputs. Neural network modellers mostly reject the employment of overt rules and symbols to the usage of distributed representations where concepts are characterized as activation-patterns in the network.

The development of artificial neural networks began more than 50 years ago, motivated by a desire both to understand the brain and to emulate some of its strengths. In other words, ANNS are biologically inspired – consisting of components that operate in a manner analogous to the most basic functions of a biological neuron. The components are arranged to resemble the anatomy of the brain to varied extents. According to Wasserman (1989), regardless of this superficial resemblance, artificial neural networks reveal a remarkable number of the brain's features – including the ability to learn from experience, to generalise from earlier examples to new ones, as well as the capacity to abstract significant attributes from inputs containing extraneous information.

The application of artificial neural networks is of interest to researchers in many diverse areas for many different reasons. Nowadays, due to the scope of their applicability, neural networks are commonly utilised in fields such as engineering, economics, business, medicine and the Social Sciences. The renewed interest in artificial neural networks can be attributed to factors like the development of high-speed digital computers, the development of training techniques to establish more sophisticated network architectures and the availability of better technology to produce specialised hardware for neural networks. At this point, the question can be posed what constitutes a neural network and why is it applied in such diverse fields of study?

An artificial neural network is an *information-processing system* that has certain performance characteristics in common with biological neural networks (Fausett, 1994: 3). Another definition is offered by Garson (1998:24). He states that a neural network is a *parallel distributed processing system* composed of processing entities called neurons, with connection strengths (weights) linking the neurons. These connections are modified to store experimental knowledge and make it accessible for consequent use in prediction and classification. Artificial neural networks were developed as generalisations of mathematical models of human cognition or neural biology, based on the following assumptions:

- *information processing occurs at many simple elements called neurons;*
- *signals are passed between neurons over connection links;*
- *each connection link has an associated weight which typically multiplies the signal transmitted;*
- *each neuron applies an activation function to its net input (the sum of weighted input signals) to determine its output signal.*

Eysenck & Keane (2000: 9) define the characteristics of artificial neural networks as follows:-

- *The network consists of elementary or neuron-like units or nodes connected together so that a single unit has many links to other units.*
- *Units affect other units by exciting or inhibiting them.*
- *The unit usually takes the weighted sum of all of the input links, and produces a single output to another unit if the weighted sum exceeds some threshold value.*
- *The network as a whole is characterised by the properties of the units that make it up, by the way they are connected together, and by the rules used to change the strength of connections among units.*
- *Networks can have different structures or layers; they can have a layer of input links, intermediate layers (hidden units), and a layer of output units.*
- *A representation of a concept can be stored in a distributed manner by a pattern of activation throughout the network.*
- *The same network can store many patterns without them necessarily interfering with each other if they are sufficiently distinct.*
- *An important rule used in networks is called backward propagation of errors.*

More specific neural network applications include signal processing, speech recognition, speech production, control and pattern recognition. Pattern recognition consists of various types of tasks, for example storing and recalling data or patterns, classifying patterns, performing general mappings from input- to output-patterns, grouping similar patterns and finding solutions to constrained optimisation problems. Social scientists find neural networks attractive because of their relevance to commonly encountered problems. Generally, in this field, neural network models may outperform traditional statistical procedures where problems lack discernible structure, data are incomplete, and various competing inputs and constraints related in complex, non-linear ways prevent formulation of structural equations (Garson, 1998). Neural network models are universal, non-parametric and robust. They even work with data that is noisy, overlapping, non-linear and non-contiguous, because processing is spread over a large number of processing entities - making these models relatively fault-tolerant. Also, there is no constraint on the number of input variables, which may include nominal-level data.

2.2 BIOLOGICAL PRINCIPLES OF NEURAL NETWORKS

2.2.1 Neural network approaches and connectionism versus conventional AI techniques

As stated, artificial neural networks are information-processing systems inspired by the operation, functionality and physiology of biological neural networks, or the human brain. Neural networks represent biological neural systems to varied degrees. Some scholars emphasize the biological credibility of neural modelling, while others rather place priority on the ability of the network to execute useful tasks. Rolls & Treves (2001:2) conceptualise this distinction in their discussion of *neuronal network approaches* versus *connectionism.* According to these authors, a neuronal network methodology focuses on the computation behaviour of authentic neural networks in the brain, with the aim to attain a fundamental and realistic foundation to understand the functionality of the brain. Connectionism, on the other hand, strives to realise cognitive performance by examining processing in neuron-like computing systems.

The differentiation between connectionism and conventional Artificial Intelligence (AI) methodologies, though, is perhaps more significant than the distinction between connectionist methodologies and neuronal network approaches – which could be argued of both fundamentally belonging to the greater paradigm of connectionism. According to Schneider (1987), the novel way of conceptualising intelligence from a *dynamic systems*- and *brain architectural perspective* instigated a paradigm crisis in Cognitive Science. Arbib (2003:15) claims that the modern study of neural networks is dominated by the notion of being dynamic and adaptive systems. In such a system, the organism (which could also be a machine) is affected by facets of its present environment in the form of inputs to- and outputs from the organism. In turn, the activities of the organism will also influence the functionality of its environment. According to Arbib, an authentic dynamic system encompasses five essential constituents:

- *a collection of inputs – environmental variables that effects the system's functionality;*
- *a collection of outputs – system variables that influence the environment and need to be examined;*
- *a set of states – internal systemic variables which determine the association between inputs and outputs;*
- *a state-transition function which establishes the nature of change whenever the system is presented with inputs;*
- *an output function that determines the output of the system in a particular state.*

Based on an immense parallel-processing paradigm, connectionism required a methodological change from symbolic rule-based systems developed in a traditional AI realm, to one found on dynamic systems – for example those utilised in Biology, Neuroscience, Physics, and Chemistry. ANNs constitute one class of these dynamic systems. Rumelhart (1989:135) gives a more comprehensive explanation of the connectionist paradigm, which is abided by in this thesis:

> *The basic strategy of the connectionist approach is to take as its fundamental processing unit something close to an abstract neuron. We imagine that computation is carried out through simple interactions among such processing units. Essentially the idea is that these processing elements communicate by sending numbers along the lines that connect the processing elements…The operations in our models then can best be characterized as 'neurally inspired'…all the knowledge is in the connections. From conventional programmable computes we are used to thinking of knowledge as being stored in the state of certain units in the system…This is a profound difference between our approach and other more conventional approaches, for it means that almost all knowledge is implicit in the states of the units themselves.*

Including a description of a *connectionist system:*

> *One of the most natural ways of thinking about what connectionist systems do is as processing patterns: classifying and categorizing them, modifying them, and associating them with other patterns* (Todd & Loy, 1991:39).

Apart from being the initial inspiration for artificial neural networks, biological neural systems advocate certain traits that have noticeable computational advantages. A review of the characteristics of the human brain with a focus on biological neurons will help to elucidate the features of artificial neural networks.

2.2.2 A look at the human brain

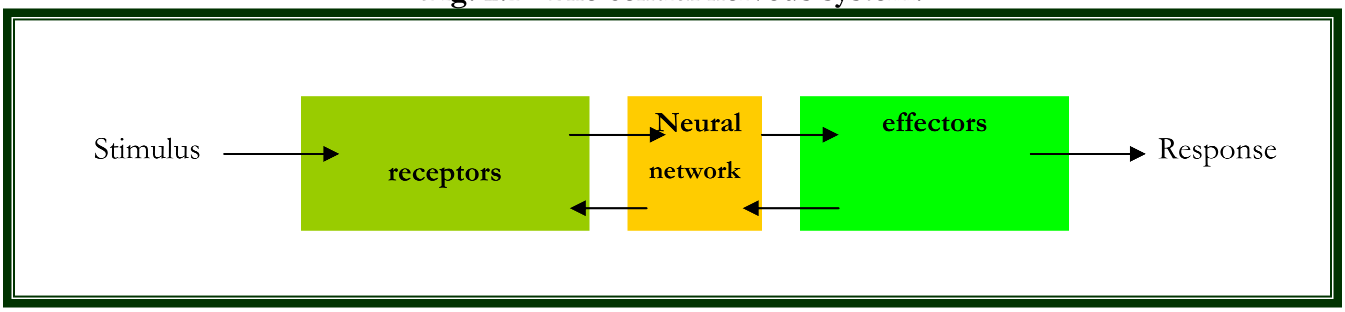
The human nervous system constitutes an intricate network intertwined through the whole body, which regulates all aspects of human existence. Governing the network is the central nervous system that consists of the brain and spinal cord. It communicates with the peripheral nervous system through 12 pairs of cranial nerves and 31 pairs of spinal nerves, which leave the brain and spinal cord. Thus the central nervous system delivers and receives messages by way of the branching fibres of the peripheral nervous system that reaches to the body extremities. In addition to these, the autonomic nervous system is concerned with involuntary functions and can be divided into the sympathetic- and parasympathetic systems.

The brain is a vastly developed, dense mass of nerve cells which forms the upper end of the central nervous system. Archaeological research reveals to us that the hominoid brain volume has increased about one percent every 50 000 years, thus in the last 50 000 years the human brain has remained fundamentally invariable. The brain varies in weight between 1 and 2 kg, with an average of 1349gm for men and 1206 for women, with a volume of approximately $1400(cm)^3$. Research shows no systematic correlation between intelligence and brain size, gender or race (Harvey, 1994).

The human brain can be divided into three major anatomical divisions. The forebrain encloses the cerebral cortex, with the neurons (cells fundamentally responsible for the brain's signal processing) near the outer surface. Interconnection pathways (axons) connect different brain areas. The cerebral cortex constitutes nearly three-quarters of the human nervous system, and can be separated into up to 12 layers in some areas. The surface density of neurons is estimated at 30 000. The forebrain is mainly responsible for sensorial processing and higher cognitive tasks. The midbrain consists of the thalamus and hypothalamus – the input/ output gates and internal regulators. The brainstem regulates consciousness and the cerebellum regulates motor control. Together these structures form the hindbrain. In the modelling of brain regions and functionality, areas are differentiated by the characteristics of nerve cells and fibre structure, the standard 52 -region mapping being that of Brodmann (as cited in Nowinsky, 2001).

Following this anatomical description, a systemic classification of the brain reveals its functionality. The main classifications are sensory, motor, behavioural, internal regulation and emotional – every system is disseminated over several brain regions. The brain requires input (I)- and output (O)- signals to operate, classified by three types of nerve endings. Exteroceptors transport information from the outside environment. Interoceptors transport signals from inside the body and proprioceptors carry information about joint pressure and muscle tension. The direction of signals can be afferent (input) or efferent (output). The main IO-connections to the environment are the cranial nerves that link the brain to sense organs in the head, and those along the spinal cord. The spine receives signals, transmits instructions to the muscles and makes austere decisions like reflex actions. The central nervous system can be depicted as a three-phased system, as illustrated in the following diagram.[14]

Fig. 2.1 The central nervous system.



Fundamental to the system is the neural network (brain), positioned centrally. This network receives and perceives information from the sensory receptors, and act on it by making relevant decisions.

[14] The illustration is based on Haykin (1999: 6) and Smith (1999: 4).

Arrows aiming to the right illustrate the forward transmission of information-bearing signals through the system. Arrows pointing left resemble feedback occurring in the system. The receptors translate stimuli from the body and environment into electrical impulses that transmit information to the neural network. Effectors convert electrical impulses produced by the neural network into distinguishable responses.

In the second stage of this three-phase process, information-processing takes place in the brain – this step is the most noteworthy to examine from the viewpoint of modelling intelligence. When the brain receives input stimuli, this data is assessed and compared with existing knowledge and stored memory. In this environment and with the appropriate devices in place, learning and thinking can be accomplished. According to Smith (1999), learning is the modification of behaviour as a result of experience. During learning, a behavioural change occurs as well as a biological modification in the brain. During the information-processing phase, synapses linking particular parts of the brain become stronger while others get weaker, to reflect the experience. This strengthening and weakening of synapses is the way in which the brain learns from experience and permanently stores new information. A similar principle is employed in the design of artificial neural network models. By using austere prototypes of the construction and behaviour of the brain, artificial neural networks can merge the speed advantages of serial computers with the learning and reasoning capability of humans.

2.2.3 Biological neuron

In the early 1900's two important findings in the understanding of the functionality of the human brain were made. In 1906[15] the Spanish neuroanatomist Santiago Rámon y Cajal [1852-1934] first introduced the idea of the nerve cell or neuron as the basic structural building block of the human brain, and in England the neurophysiologist Charles Sherrington [1857-1952] provided the basic physiological understanding of a synapse – the junction between neurons (Arbib, 2003:10).

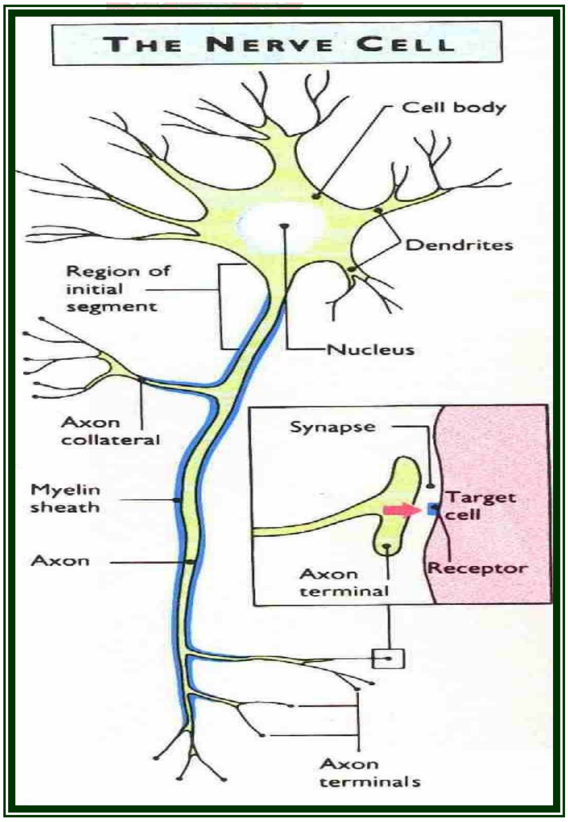
Until the late 1990s, biological neurons were typically described as being five to six orders of magnitude slower than silicon logic gates – neural events occur in the millisecond range, whereas phenomena in a silicon chip occurs in the nanosecond range (Haykin, 1999:7 & Solso, 1991:482). The massive number of neurons with immense interconnections between them compensate for this relatively slow neural operational speed of the brain. The number of neurons in the cortex is estimated at 10 billion, with 60 trillion connections (synapses) between them. Transmission paths may extend over more than a metre.

[15] There is uncertainty concerning this date, Haykin (1999) stated it as 1911.

A single neuron regularly has between 5000 and 20 000 inputs (Rolls & Treves, 2001). According to Stubbs (1988), neurons could be organized into about 1000 major sections, each having approximately 500 neural networks consisting of 100 000 neurons.

A biological neuron has three significant elements that are important for the understanding of the functionality of an artificial neuron, namely *dendrites*, *axon* and *soma,* as illustrated in figure 2.2.[16] Dendrites and axons are two types of cell filaments that are distinguishable on morphological grounds. A dendrite has an irregular surface and more branches than the smoother and longer axon. Dendrites are the main receptors of the neuron and serve to connect its incoming signals. The axon or nerve fibre is the outgoing connection for signals emitted by the neuron and terminates at the synapse. A synapse is the unit that mediates the interaction between neurons. The majority of synapses in the cerebral cortex are chemical and not electrical. According to Rumelhart & McCleland (1995b: 338), there are many different types of synaptic contacts in the cerebral cortex – which are *morphologically* classified into two basic categories. For a detailed description of these types, the reader is referred to the aforementioned authors.

Fig. 2.2 Biological neuron



At the synapse the axon makes contact with the dendrites of cell bodies of other neurons, or with secretory- or muscle-cells. An electrical signal in the axon causes the release of a chemical transmitter

[16] The illustration is taken from Crofton (1995: 220).

that carries the message to the next stage. The cell body (soma) aggregates incoming signals and fires (transmits a signal over the axon to other cells) when sufficient input is received. When a neuron fires, its axon becomes electrically active and acts as the output of the neuron, sending signals to other neuron cells. Signal-transmission is achieved by an action potential resulting from differential concentrations of irons (mainly potassium, sodium and chloride) on either side of the neuron's axon sheath. Communication in neurons is therefore achieved by the transmission of electrical and chemical impulses along connecting synapses.

It is often assumed that transmitted signals can be treated as *binary* because a cell either fires or doesn't fire at any moment in time (Fausett, 1994:5). The frequency of firing, however, fluctuates and can be seen as a signal of lesser or greater strength, which correlates with looking at discrete time steps and summing all received or sent signals at a particular moment in time.

The features of biological neurons propose a few important characteristics of the processing elements of artificial neural networks, suggested by Fausett (1994:6):

- *the processing element receives many signals;*
- *signals can be adjusted by a weight at the receiving synapse;*
- *when adequate input, the neuron sends out a single output;*
- *the output from a particular neuron may go to many other neurons;*
- *information-processing is local (although other means of transmission like the action of hormones may suggest means of overall process control);*
- *memory is disseminated as long-term memory residing in the neurons' synapses or weights; or as short-term memory corresponding to the signals sent by the neurons;*
- *a synapse's strength may be adapted by experience;*
- *neurotransmitters for synapses can be excitatory or inhibitory.*

In addition to these and those previously mentioned by Wasserman (1989), artificial neural networks – similar to biological systems – are also fairly fault tolerant. Biological neural systems can distinguish between input signals that are a bit different to signals encountered before. The human neural system can also endure certain damage: in spite of a constant demise of neurons, other neurons can to some extent be trained to take over the functions of the impaired cells. Comparable to this, artificial networks can be constructed to be insensitive to minor damage to the network, and can be retrained in cases of substantial damage, such as loss of data and connections.

2.3 HISTORICAL DEVELOPMENT OF ARTIFICIAL NEURAL NETWORKS

In chapter 1.3, it is mentioned that both the fields of Artificial Intelligence (AI) and artificial neural networks (ANNs) were formally launched and brought to public attention in 1956. Before the historical evolution of artificial neural networks can be discussed, it would be worthwhile to familiarise the reader with the distinction between this field and Artificial Intelligence.

2.3.1 Models of human cognition: Symbolic AI systems and ANNs[17]

Many authors[18] on the subject of Artificial Intelligence describe artificial neural networks as a research constituent or extension of the former, and AI belonging to the bigger sphere of the Cognitive Sciences.[19] Although sometimes rather fuzzy, there is a significant difference between these two fields of study.

Arbib (2003:11) describes AI as the study of how computers could be programmed to exhibit intelligent behaviour without unavoidably attempting to present a parallel between structures in the program and structures in the brain. This description is of relevance to AI in a more *traditional-* or 'symbolic' sense which depends strictly on computation over symbolic structures like logic formulae. According to Barnden & Chady (2003:113) there is no clear-cut definition of AI, just as there does not exist an explicit definition of human intelligence. These authors attempt to provide a more inclusive definition of AI and argue that there is nothing in this description that prevents the computational system to be a neural network:

> *…AI consists of the development, analysis, and simulation of computationally detailed, efficient systems for performing complex tasks, where the tasks are broadly defined, involve considerable complexity and variety, and are typically similar to aspects of human cognition and perception.*

According to Sage (1990), the goal of AI is the development of paradigms or algorithms that require machines to perform cognitive tasks, at which humans are presently better. Sharples et al. (1994:1, 21) states that the aim of AI is to discover the processes, systems and principles that make intelligent behaviour possible and to use computers as tools in the modelling of these processes. Accordingly, the

---

[17] This distinction can also be described as symbolic AI systems versus connectionism – refer to section 2.2 in this regard.

[18] Arbib (2003); Sharples et al. (1994); Solso (1991); Dreyfus & Dreyfus (1986), & McCorduck (1979).

[19] The reader is referred toVon Eckardt (1993), Solso (1991),& Posner (1989).

main assumption of AI is that intelligence can indeed be represented in terms of symbol structures and symbolic operations, which can be programmed in a digital computer.

A system should demonstrate three functions to qualify as being AI. It must be able to store information (*representation*), apply the stored information in problem solving (*reasoning*) and attain new knowledge through experience (*learning*) (Haykin, 1999:34). Rather that providing a comprehensive review of these components (the reader is referred to Arbib (2003) and Haykin (1999) in this regard), the following discussion will focus on three differences between symbolic AI machines and ANNs as cognitive models.

Level of explanation

Conventional AI focuses on the creation of symbolic representations of constructs. From a cognitive perspective, AI assumes the subsistence of mental representations, and models cognition as the sequential processing of symbolic representations. In contrast, ANNs focus on the development of parallel distributed processing models, which assume that information processing occurs through the interaction of numerous neurons that send excitatory or inhibitory signals to other neurons in the network. Neural networks are also concerned with the neurobiological explanation of cognitive processes.

Processing style

Information processing in mainstream AI is sequential, similar to typical computer programming: operations are executed in a step-by-step method. In ANNs, parallel processing is conceptually essential and forms the basis of its flexibility. Similar to the brain, computations can be done in parallel with many 'transactions' taking place at the same time. Parallelism is frequently extensive, incorporating thousands of neurons - which give neural networks their important trait of robustness - with the computation distributed over many neurons, it is not problematic if the conditions of some neurons in the network deviate from their expected values. Noisy or incomplete inputs may yet be recognised, a damaged network can still be operating functionally and learning does not have to be flawless.

Representational structure

In classic AI, symbolic representations have a *quasi-linguistic* structure (Haykin, 1999:37): like expressions of natural language, the representations of classical AI are usually complex, built systematically from simple symbols. Thus, symbolic AI is the formal manipulation of a language of algorithms and knowledge representation in a *top-down* fashion. In contrast, neural networks are parallel-distributed processors, operating in a *bottom-up* fashion with an inherent ability to learn.

For a more inclusive comparison between the advantages of both of these paradigms, the reader is referred to an interesting article entitled *Artificial Intelligence and Neural Networks* by Barnden & Chady (2003). The authors provide a survey of the distinctions between symbolic AI systems and ANNs, the benefits of each, as well as ways of attempting to bridge the gap between these two fields.

2.3.2 Evolution of artificial neural networks

A number of occurrences in several diverse disciplines have contributed to the present course of neural network research and application. The considerable body of academic literature available on the topic - originating from these numerous fields of study - provides us with some excellent writings on the historical development of ANNs. This review will mainly draw on Smith's (1999) division of the history of neural networks into five business-related developmental stages, in fitting with the focus of the thesis on a commercial musical environment. In addition to Smith, it will also assimilate reviews by Haykin (1999), Stein & Ludic (1998), Garson (1998), Beltratti et al. (1996), Warner & Misra (1996), Rumelhart & McClelland (1995a), Fausett (1994), Davalo & Naïm (1991), Maren et al. (1990), and Wasserman (1989).

The first developmental stage preceded 1945. During this phase most of the initial development and preliminary research, which laid the foundation for future neural network research, was accomplished. In 1834 Babbage [1791-1871] created the fundamental design principles of analytic machines which became the precursor to the modern digital computer. The capacity of these machines to automate calculations led to their widespread use by 1900, and International Business Machines was established in 1914 to secure this new market. Prior to this, psychologists like the American James [1842-1910] had been researching human brain functionality and learning. James noticed the essentiality for change in mental associations and reflected on brain processes that could account for it. At this time, the term *neuron* had not arrived in America from across the Atlantic, so he described *points* in the cerebral cortex and the connections between them (Stein & Ludic, 1998:21). In the following quotation, the reader can substitute *point* with *neuron* to arrive at the conclusion that the activity of a neuron is equal to the sum of its weighted input.

> *The amount of activity at any given point in the brain-cortex is the sum of the tendencies of all other points to discharge into it, such tendencies being proportionate (1) to the number of times the excitement of each other point may have accompanied that of the point in question; (2) to the intensity of such excitements; and (3) to the absence of any rival point functionally disconnected with the first point, into which the discharges might be diverted (James, 1892/ 1984: 226).*

Neurons not being officially identified as yet, James foresaw an organising principle of neural networks before he knew about their existence, and developed a learning rule in this regard:

When two elementary brain processes have been active together or in immediate succession, one of them, on re-occurring, tends to propagate its excitement into the other (James, 1892/ 1984: 226).

In the 1890s, partially inspired by the findings of the neuroanatomist Rámon y Cajál [1852- 1934], many scientists, psychologists and physicians published writings related to the concept of the neuron. Rámon y Cajal first introduced the idea of the nerve cell being the basic structural entity of the human brain with synaptic gaps between them. In 1894 the physiologist Exner [1846- 1926] issued a treatise entitled *Project for Physiological Explanations of Mental Phenomena*, which included numerous illustrations of neural networks, assumed to accomplish a range of mental phenomena. The psychologist Freud [1856- 1939] also attempted to encompass the latest neuroscientific research findings into a dissertation called *Project for a scientific Psychology* in 1895. In this work, he tried to depict the foundations of a comprehensive, interdisciplinary Neuroscience of the mind. According to Stein & Ludic (1998), Pribram & Gill (1976), Hobson & McCarley (1977) and Sulloway (1984), Freud's first major work on the foundations of psychoanalysis, *The Interpretation of Dreams* (1900/ 1991), is in various ways a neurocognitive model in the mask of psychological theory. The notion of neurons associated with each other to establish a network was very popular in the main paradigm of Psychology for twenty years following 1880, namely A*ssociation Psychology*. *Association* obtained a novel *biological* meaning in that brain parts (neurons) rather than ideas were thought to be connected in a particular way.

In 1904 Pavlov [1849- 1936] received a Nobel Prize[20] for his theories on conditional learning, directive for subsequent research in neural networks. Turning [1912- 1954] also explored computing machines incorporating the human brain as paradigm, which laid the groundwork for the establishment of the field of AI. The first stage of preliminary research concluded with the neurobiologist McCulloch [1898- 1972] and statistician Pitts' [1924, n.d.] attempts to portray the functionality of the brain in mathematical terms (1943). Working at the University of Chicago from the late 1930's, they used an analogue to the human brain's neuron and demonstrated that a network of artificial binary-valued neurons could perform calculations. They noticed the increased computational power of combining many simple neurons into neural systems and designed what is acknowledged as the first artificial neural network. The McCulloch-Pits neuron is discussed as a separate entry in 2.2.3. However, these early networks did not demonstrate any learning ability. This drawback, together with a lack in sufficient computing resources, suppressed further experimentation at this stage.

The subsequent phase is typified by the era of computer simulation. Wilkes invented the first operational stored-program computer in 1946 and the development of electronic computers proceeded

[20] Category: physiology/medicine.

quickly from there. General Electric Company became the first business to employ the usage of computers with the computerisation of their payroll system in 1954. Improved computing permitted scholars of neural networks like the Canadian physician and psychologist Hebb [1904-1985] to experiment with neural network theories. In *The Organization of Behavior* (1949) he proposed a physiological learning rule (*Hebb's rule*) to allow neural network synaptic weights to be adapted to exhibit the learning process examined by Pavlov. Hebb suggested that the connectivity of an organism's brain is constantly changing as it learns differing functional tasks, resulting in the development of neural groupings. The Hebb rule was the first formal presentation of the concept of synaptic modification, in contrast to the McCulloch-Pits model that used fixed weights, and the forerunner of the *backpropagation* rule. A simplified version of Hebb's rule is as follows:

> …*when a cell A excites cell B by its axon and when in a repetitive and persistent manner it participates in the firing of B, a process of growth or of changing metabolism takes place in one or in both cells such that the effectiveness of cell A in stimulating and impulsing cell B, is increased with respect to all other cells which can have this effect* (Davalo & Naïm, 1991: 26).

Minsky [1927 -] developed the first neurocomputer founded on these principles in 1954. The Dartmouth Summer Research Project on Artificial Intelligence of 1956 witnessed the official inauguration of the fields of AI and neural networks. The directive of the conference was *to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it* (Garson, 1998: 3). At this meeting Rochester of IBM Research and Development presented the first successful computer simulation of synaptic change in a neural system, which employed a modified version of Hebb's idea. Neurons and connections were simulated and patterns of co-ordinated activity appeared in the simulated 'cells' after learning had occurred, although the mechanisms of such synaptic changes in biological neurons were unknown at the time.

The psychiatrist Kandel [1929 -] stimulated development in this area by demonstrating how learning and synaptic change occurred in parallel in a simple organism (sea snail). With this he undoubtedly confirmed the correlation between learning and synaptic modification. In the same year Uttley (1956) demonstrated that binary patterns could be classified by a neural network of which the synaptic links were modified in response to presentation of patterns, and Taylor (1956) published the first review on associative memory. Rosenblatt's [1928 - 1969] *Perceptron* (two-layered neural network)- model (1958), as well as numerous unsophisticated examples illustrating the learning capacity of neural networks, was introduced the following year. Rosenblatt (1958) demonstrated that a neural computer system can learn to classify inputs through induction from example rather that through the usual top-down programmed algorithmic instructions commonly used in statistical packages.

Widrow [1929 -] initiated an expanded application of neural networks - meteorological forecasting- at Stanford University in 1962. His *Adaline* (adaptive linear neuron) system was a single-layered neural network model applying a more sophisticated learning rule than Rosenblatt's perceptrons, and the consecutive *Madaline* represented a two-layered version of the former. Widrow and his colleagues also applied neural analysis to character- and speech recognition. By this time, and for the remainder of the 1960s, the disciplines of AI and neural networks caused great excitement amongst researchers and the general public alike.

The third stage- or quiet years- followed after the publishing of *Perceptrons* by Minsky & Papert in 1969, which produced mathematical evidence that neural network models are unable to learn problems that contain linearly inseparable information.[21] Many scholars at the time overlooked the fact that their criticism was confined to two-layered neural systems using linear activation functions. Although enthusiasm for the field diminished during these years, important progressions in the computer industry occurred. Intel Corporation developed the Microcomputer in 1971 and International Business Machines (IBM) the Personal Computer in 1981. Globally the incorporation of these machines in the business world became common and numerous computer- and software companies were established during these years.

Researchers began to explore different neural network models to surmount the constraints described by Minsky and Papert, and constructed more complex models incorporating middle or 'hidden' layers, providing the capacity to handle more difficult knowledge representation problems. In contrast with the perceptron- model, these network models utilised a non-linear activation function. Grossberg continued significant research on neural network at this time by exploring self-organizing networks, adaptive resonance and the Cohen-Grossberg theorem, which shows that external inputs to certain types of networks will converge toward equilibrium. His ART (adaptive resonance theory) model was in contrast with the supervised, multi-layered *perceptrons* and learned without supervision on a single passage of the data. Furthermore, Anderson et al. (1977) and Grossberg (1980) applied neural networks in the field of Psychology. Later on, in the 1980s, Kohonen [1934 -] also examined the ideas of self-organization in the human brain and neural network models, based on earlier work by Willshaw and von der Malsburg.

[21] *Linear separability* indicates that there exists a line in two dimensions (hyperplane) that can completely delineate the classes that the classifier aims to recognize (Warner & Misra, 1996: 285). Linear separability represents a limited type of decision margin and does not offer an optimal performance in most practical applications (Bishop, 1999).

The development of the field of AI featured as a background issue in the contribution towards a renewed interest in neural computing in the 1980s (Garson, 1998: 6). Conventional AI employed composite *top-down, if-then* algorithms arranged together to form expert systems which could mimic human decision-making. Originally, AI's algorithmic method advanced quickly, but by the 1980's it had become evident that earlier hopes were unlikely to be fulfilled. Irrespective of remarkable achievements in some clear-delineated areas, in less comprehensive defined problems, algorithmic AI didn't progress as expected and thus indirectly triggered new courses for research in neural networks. In 1982, the physicist Hopfield [1933 -] explored theories around storing and retrieving memory (Tank & Hopfield, 1987). In association with Tank, he developed neural networks based on fixed weights and adaptive activations which could serve as associative memory nets to resolve constrained satisfaction problems such as the *Travelling Salesman Problem*[22] (Fausett, 1994:25). Together with an article in *Scientific American* (1987) that attracted popular attention to neural networks, this research stimulated a great revival in the field.

Neural network research progressed rapidly from 1983 to 1990, which marks the fourth developmental stage. In 1985 backpropagation was discovered independently by Le Cun (1986) and Parker (1985), which presented a new learning rule for neural networks which overcame the limitations described previously.[23] Rumelhart, Hinton and Williams (1986) described the back-propagation algorithm in 1986 and suggested its relevance for machine learning. This algorithm accommodated the learning of complicated problems without the constraints of perceptrons. With the growth of the field during this stage, significant theoretical writings and conferences on the topic emerged. A few researchers also developed non-deterministic neural nets for the solving of combinatorial optimisation problems. In these models, the weights were changed on the basis of a probability density. The networks were labelled as Boltzman machines and drew on ideas like *simulated annealing* and *Bayesian decision theory.*[24] The Boltzman machine was the first successful realisation of a multi-layered network. By 1989, the neural network modelling movement had completely surmounted from the setback suffered during the 1970s. The commercial world, however, did not incorporate the usage of neural networks on a large scale until the early 90s.

The fifth stage commenced in the 1990s with newfound fascination in the field partly incited by the preceding development of multi-layered nets and improved computational abilities. Vapnic and other

---

[22] A description of The Travelling Salesman Problem is given by Fausett (1994:335).

[23] Smith (1999) states that Werbos actually proposed the backpropagation learning rule in a Ph.D dissertation in 1974, but this work was only discovered after a publication by Rumelhart & McClelland (1986).

[24] The reader is referred to Fausett (1994:26) for a comprehensive review of these constructs.

researchers developed a computationally powerful class of supervised learning networks in the early 90s, identified as *support vector machines* (Haykin, 1999:44). Amongst others, these networks could be applied to pattern recognition and were based on the learning theory with finite sample size. An important development in the business world commenced in 1991 when banks began using neural networks for financial prediction and decision-making. Neural network companies emerged and developed user-friendly software with numerous architectures and learning rules – many designed to operate on a PC under Microsoft Windows®™. This influenced the business world enormously, and continued research in this field is mostly industry-driven. Today the commercial world depends more and more on intelligent systems like neural networks to solve a range of problems, and new research subjects are surfacing accordingly. Nowadays, researchers are developing techniques for extracting rules from neural networks and combining them with different intelligent methods like genetic algorithms, fuzzy logic and expert systems.

To conclude this historical overview, a citation by Jenkins (1991:50) is quoted to capture one description of the excitement of the neural network movement:

> …*neural networks represent a new way of thinking: a wildly polygamous conjunction of computer science, biology, linguistics, engineering, Psychology , and statistics that had the thrill of 1960s rock and the roar of a thousand central processors hooked up in parallel.*

2.3.3 The McCulloch-Pitts Neuron

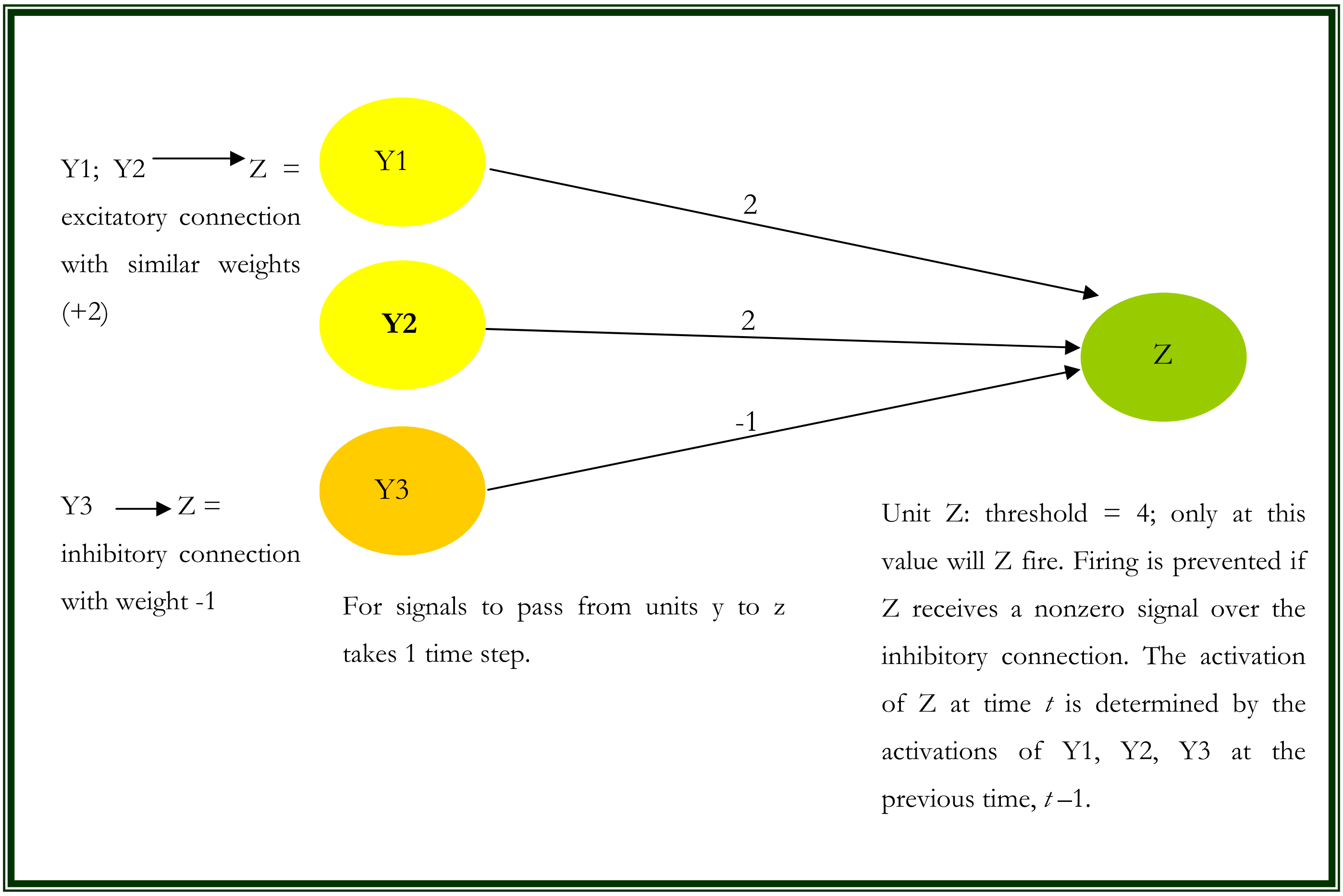
The original McCulloch-Pitts (1943) artificial neuron demonstrates significant characteristics found in contemporary neural networks, which can be abridged as follows:-

- Activation of the neuron is binary – at any stage, the neuron either fires (activation=1) or does not fire (activation=0).
- The neurons are linked by directed, weighted paths.
- A connection path is excitatory if the weight on the path is positive and inhibitory otherwise. All excitatory connections into a particular neuron have the same weights.
- Every neuron has a fixed threshold – when the net input to the neuron is larger that the threshold it will fire.
- The threshold is set so that inhibition is unconditional – any non-zero inhibitory input will prevent firing.
- It takes one time step for a signal to pass over one connection link.

The fundamental nature of the McCulloch-Pitts parallel to biological neurons is described in the following paragraph, and illustrated in fig. 2.3.[25]

A processing unit (artificial neuron) can be programmed to release a signal (fire) when its inputs reach a certain threshold level. In a biological system, dendrites connect neurons and this can be emulated in the artificial system through programmed connections. To model the biological occurrence of synapses with different strengths, with some permitting a large signal to pass through and others allowing a weak signal, connections are allocated between inputs and neurons. The connections can also be programmed to be positive or negative, simulating the biological phenomenon where certain synapses are excitatory and adds to the signal received from the dendrite, while others are inhibitory and reduce the obtained signal.

Fig. 2.3 McCulloch-Pitts Neuron



---

[25] The illustration is based on Fausett (1994:27).

The McCulloch-Pitts network resembles the most basic prototype of ANNs: a network with a single layer of neurons. Although this type of ANN can accomplish various tasks, more intricate organisations of neurons offer superior computational capabilities. In the next section the structure of complex networks are portrayed.

2.4 NETWORK ARCHITECTURE

Network architecture (sometimes referred to as the network structure or network model) is the arrangement of neurons into layers and the connection patterns within and between these layers (Fausett, 1994). These configurations are very closely associated with the learning rule or algorithm that is used to train the network. The topic of network architecture is an extremely extensive one – Sarle (2004) states that there is no accurate description of exactly how many different types of networks exist, as new variations are invented every week. This section serves as a broad introduction to the general features of typically encountered neural network architectures. The attributes of specific network architectures, as applied in musical research, will be dealt with comprehensively in chapter 3.

In a typical ANN, the neurons (intermittently referred to as processing entities/cells/units/nodes) can be visualised as being organised into layers, where neurons in the same layer exhibit similar functionalities. Units are identified as being either *input-* (I) (obtaining external signals) or *output-* (O) from which the response of the network can be inferred. Another way by which these two categories can be comprehended is to say that inputs are the alleged predictor variables, while outputs are the network's approximations of the dependant variable.

Networks can be *single-layered* or *multi-layered.* A single-layered network has only one layer of connection weights. Input units do not execute any computation and are therefore usually not identified as an independent layer in the network. In a typical single-layered network, input units are wholly connected to output units but not to other input units – the same applies for output entities. The Hopfield architecture represents an exception on this imperative, being a single-layered network with all units operating as both input- and output units. Multi-layered networks encompass one or more hidden layers, the computational nodes of which can be described as *hidden neurons*. Hidden neurons mediate between the I- and O- entities, making the network capable of handling more complicated problems (in other words, to obtain higher-order statistics).

The main issues in determining the behaviour of a neuron are its pattern of weighted connections over which it sends and receives signals, and an activation function which sends the summed weighted inputs to the subsequent layer. Generally, neurons in the same layer have similar activation functions and connection patterns. In many networks, the activation of each unit is equivalent to an external input signal. The number of layers in the network can be described as the integer of layers of weighted interconnected linkages between the chunks of neurons, owed to the fact that the weights contain significant information. The association between these units and a corresponding weighting factor is the basis on which the ANN can perform noteworthy computations. This weight can be regarded as a connection strength between units, signifying the amount of influence of the first unit on the next, and so forth. As mentioned in 2.3.3, weights can be either positive or negative, therefore this effect is characterized as being excitatory or inhibitory.

To determine the output of a single unit, all the weighted input units are calculated through a *summation function*, variably referred to as a *combination function, linear combiner* or *adder* (Garson, 1998:26). Mathematically, this procedure can be depicted in the following equation, as described by Dolson (1991):-

$$\mathbf{Xi} = \mathbf{f}\ \Big(\sum_{j=1}^{N} \mathbf{w}\ ij\ \mathbf{x}\ j\Big)$$

All the *N* units in the network can be identified with a distinctive number between 1 and *N*. The output (x i) of the i-th unit in the network is given by the equation. *F* is a non-linear function and *Wij* is the weight from the *j*-th unit to the i-th.

Furthermore, networks are distinguished by the direction of signal-flow. In a *feedforward* network the signal only proceeds forward from input units to output units, while in a *feedback* or *recurrent* network there exist at least one closed-loop signal path from a unit back to itself. It should be apparent that the feedback loops have a substantial influence on the learning capacity and performance of an ANN. In a *fully connected* network all the neurons in each layer is linked to every neuron in the next layer. If a network is *partially connected,* a few of the communication links are absent from the network. Links between nodes in different layers are called *interlayer connections*; lateral connections between neurons in the same layer are sometimes encountered and identified as *intralayer connections*. These types of associations habitually restrain some neurons from firing, and can therefore be perceived as being representative of *competitive* networks. An additional kind of forward connection is called a *jump connection* which omits any hidden layers by linking nodes from the input layer directly with units in the output layer. Figure 2.4 illustrates a few of these concepts.[26]

[26] The illustrations are based on Haykin (1999) & Todd & Loy (1991).

Fig. 2.4(a) Feedforward architecture

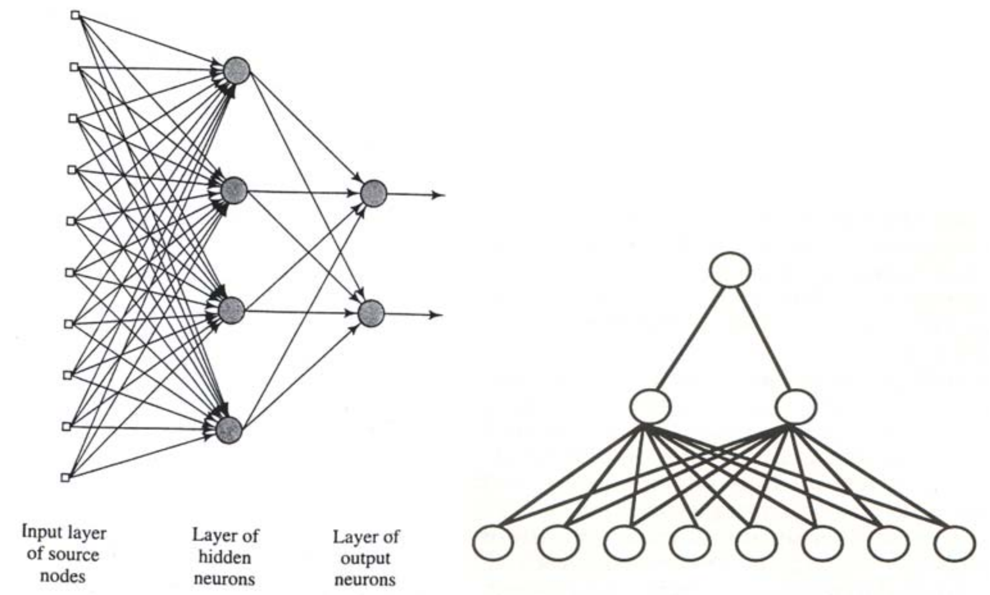
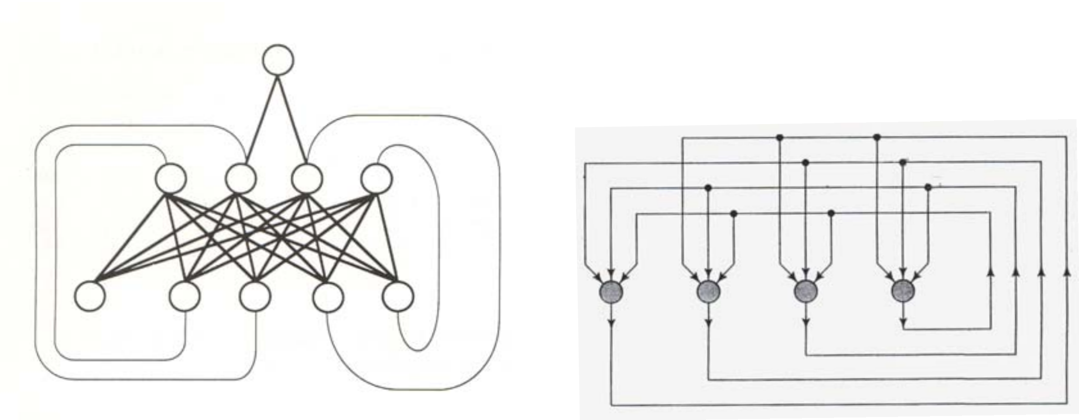


Fig. 2.4(b) Recurrent architecture



Training (the method of establishing the value of weights) is a significant factor in the differentiation of neural networks. Also referred to as the choice of *learning rule*, training depends to some extent on the chosen architecture. In *supervised* training, a sequence of training vectors with related target output vectors are used and weights are modified according to a learning algorithm. Supervised learning can also be described as *learning with a teacher*, seeing as the network is trained to generate the correct response for a given input, assuming that the teacher owns an inclusive collection of input and matching responses on which to train the network. Examples of supervised networks for pattern classification are Hebb network, Perceptrons and Adaline (Adaptive Linear Neuron), and for pattern association there are variations on Hebb networks as well as heteroassociative memory networks, autoassociative networks, iterative networks and bidirectional associative memory networks.

Unsupervised training occurs when self-organising networks arrange analogous input vectors together without using training information to indicate what an archetypal member of every group looks like or to which group each vector belongs. A sequence of input vectors is presented, but without specifying target vectors. The network modifies the weights so that the most congruent inputs are assigned to the same output entity. Examples of unsupervised networks are Kohonen maps, Brain State in a Box (BSB), and adaptive resonance theory (ART-networks). For a full review on these various network architectures the reader is referred to the writings of Bishop (1999), Haykin (1999), Arbib (1995), Fausett (1994), Davalo & Naïm (1991) - or any other standard academically acclaimed text on the topic.

2.5 PRACTICAL APPLICATION OF ARTIFICIAL NEURAL NETWORKS

This chapter has illustrated the significance of the exploitation of artificial neural networks by researchers and end users over the scope of the natural as well as the Social Sciences. In conclusion, a few practical applications of neural network analysis that have been successfully used in the Social Sciences, which are the focal point of this thesis, will be mentioned. These studies are taken from Smith (1999), Stein & Ludic (1998), Garson (1998) and Beltratti et al. (1996).[27]

ANNs are becoming progressively more common in a variety of areas within the scope of Economics and Business. These research studies are mainly published in business journals and information technology periodicals. Examples of applications include the modelling of consumer choice and

[27] Standard academically acclaimed technical terminology, as used in the original texts, is exploited in this section.

production functions; target marketing; document retrieval; employee classification- and selection; bankruptcy prediction; economic modelling and decision-making; risk assessment; stock selection and sales forecasting. In Banking and Finance, neural networks have been used in trading and financial forecasting, loan applicant decision making, and financial fraud detection. In the Insurance industry there are also many potential usages of neural networks, such as policy holder-segmentation, prediction of claim frequency, fraud- or special circumstance-detection, and customer retention.

In the field of Sociology ANNs have been applied to problems like the modelling of human decision-making and learning; the prediction of white collar crime; the prediction of violent criminal behaviour based on criminal history, demographic-, family- and work variables and psychometric scales; selection of criminal investigation targets; the screening of decisions regarding child abuse and the explication of patterns of social mobility and inequality.

The uses of neural network analysis in Political Science includes the analysis of voting behaviour; the prediction of the outcome of law cases; the selection of optimal legal strategies; event analysis in international relations; prediction of the likelihood of passing bar examinations and the prediction of administrative success of candidates for local school principals.

In Psychiatry there has lately been a shift from the leading psychodynamic school of thought towards a neurobiological paradigm that has brought about some significant improvements in the understanding and management of mental disorders (Stein & Ludic: 1998). This field applies many different neural network models to various areas in Psychiatry - for example the utilisation of network models in diagnosis, in the modelling of psychotherapeutic processes and psychopharmacological data, and the modelling of pshychodynamic phenomena.

The field of Psychology has also incorporated neural network models for psychiatric diagnoses; predicting psychiatric treatment outcomes; the modelling of human memory-, -development, -recognition and unipolar depression; information acquisition; chromatic- and depth perception; the teaching of Cognitive Psychology ; identification of structure in personality data; predicting employee misconduct; test validation and instrumentation; the simulation of spatial learning, and spoken word recognition.

Besides this small number of chosen examples from the Social Sciences, there is a vast array of ANN applications in other fields, for example Industrial Science, Manufacturing, Agriculture, Aerospace, Weather forecasting, Banking, Insurance, Sports, Entertainment, Defence, Robotics, Speech recognition, Materials Science, Chemistry, Physics, Statistics, Engineering, Biology, Medicine, Neurophysiology, Electronics, Transportation, Oil and Gas Exploration, and Telecommunications - which do not fit the scope of this research endeavour. It must be clear, though, that artificial neural network models present the social scientist, amongst others, with a tool which has been proven to be powerful across a broad range of problems - frequently to outperform standard investigative procedures - and to be appropriate even for ambiguous data environments commonly found in the Social Sciences. It is therefore palpable that researchers in the domain of music also recognised the advantages, and exploited the usage of artificial neural networks.

References

Anderson, J. A., Silverstein, J. W., Ritz, A. & Jones, R. S. (1977). Distinctive features, categorical perception, and probability learning: some applications of a neural model. ***Psychological Review, (***84), 413-451.

Arbib, M. A. (2003). (Ed.). ***The Handbook of Brain Theory and Neural Networks.*** Cambridge, Massachusetts: The MIT Press.

Barnden, J. A. & Chady, M. (2003). Artificial Intelligence and Neural Networks. In Arbib, M. A. (Ed.). ***The Handbook of Brain Theory and Neural Networks,*** (98-102). Cambridge, Massachusetts: The MIT Press.

Beltratti, A; Margarita, S. & Terna, P. (1996). ***Neural Networks for Economic and Financial Modelling.*** London: International Thompson Computer Press.

Bishop, C. M. (1999). ***Neural Networks for Pattern Recognition.*** Oxford: Oxford University Press.

Crofton, I. (1995). (Ed.). ***The Guinness Encyclopedia – New Edition.*** Great Britain: Guinness Publishing Ltd.

Davalo, E. & Naïm, P. (1991). ***Neural Networks.*** Houndmills: Macmillan Education LTD.

Dolson, M. (1991). Machine Tongues XII: Neural Networks. In Todd, P. M. & Loy, D. G. (Eds). ***Music and Connectionism*** (3-19). Cambridge, Massachusetts: The MIT Press.

Dreyfus, H. L. & Dreyfus, S. E. (1986). ***Mind Over Machine.*** New York: The Free Press.

Eysenck, M.W. & Keane, M.T. (2000). ***Cognitive Psychology: A student's handbook*** (4th edition). Hove: Erlbaum.

Fausett, L. (1994). ***Fundamentals of Neural Networks.*** New Jersey: Prentice-Hall, Inc.

Freud, S. (1895). ***Project for a scientific Psychology. The Standard Edition of the Complete Psychological Works of Sigmund Freud -Volume 1.*** London: Hogarth Press.

Freud, S. (1900/ 1991). ***The Interpretation of Dreams*** (translated and edited by Strachey, J.). London: Penguin Books.

Garson, G. D. (1998). ***Neural Networks: An Introductory Guide for Social Scientists.*** London: SAGE Publications.

Grossberg, S. (1980). How does a brain build a cognitive code? ***Psychological Review,*** (87), 1-51.

Harvey, R. L. (1994). ***Neural Network Principles.*** Englewood Cliffs, New Jersey: Prentice-Hall, Inc.

Haykin, S. (1999). ***Neural Networks- a comprehensive foundation***. USA: Prentice-Hall,Inc.

Hebb, D. O. (1949). ***The Organization of Behavior.*** New York: John Wiley & Sons.

Hobson, J. A. & McCarley, R.W. (1977). The brain as a dream state generator. ***American Journal of Psychiatry,*** (134), 1335-1348.

James, W. (1892/ 1984). ***Psychology: Briefer Course.*** Cambridge, MA: Harvard University Press.

Jenkins, D. (1991). Where are neural networks going? ***AI Expert,*** (Nov.), 50-51.

Le Cun, Y. (1986). Learning Processes in an Asymmetric Threshold Network. In Bienenstock, F. et al. (Eds). ***Disordered Systems and Biological Organization.*** Berlin: Springer-Verlag.

Maren, A., Harston, C. & Papa, R. (1990). ***Handbook of Neural Computing Applications.*** San Diego, California: Academic Press, Inc.

McColloch, W. S. & Pitts, W. (1943). A Logical Calculus of the Ideas Immanent in Nervous Activity. ***Bulletin of Mathematical Biophysics,*** (5), 115 -133.

McCorduck, P. (1979). ***Machines Who Think.*** San Francisco: W.H. Freeman and Company.

Minsky, M.L. & Papert, S. A. (1969). ***Perceptrons.*** Cambridge, MA: MIT Press.

Nowinsky, W. L. (2001). ***Brain atlas for functional imaging.*** Stuttgart: George Thieme Verlag.

Parker, D. (1985). ***Learning Logic.*** Technical Report TR-87. Cambridge, MA: Center for Computational Research in Economics and Management Science, MIT.

Posner, M.I. (ed.). (1989). ***Foundations of Cognitive Science***. Cambridge, Mass: MIT Press.

Pribram, K. H. & Gill, M.M. (1976). ***Freud's Project Re-assessed.*** New York: Basic Books.

Rámon y Cajal, S. (1911). Histologie du Systèmes Nerveux de l'homme et des vertébrés. Paris: Maloine.

Rolls, E. T. & Treves, A. (2001). ***Neural Networks and Brain Function.*** Oxford: Oxford University Press.

Rosenblatt, F. (1958). The Perceptron: a Probabilistic Model for Information Storage and Organization in the Brain. ***Psychological Review,*** (65), 386 - 408.

Rumelhart, D. E. (1989). The architecture of mind: a connectionist approach. ***Foundations of Cognitive Science.*** Cambridge, Massachusetts: MIT Press.

Rumelhart, D. E, Hinton, G. E. & Williams, R. J. (1986). Learning Representations by Back-Propagating Error. ***Nature,*** (323), 533-536.

Rumelhart, D. E. & McClelland, J. L. (1986). ***Parallel Distributed Processing – Explorations in the Microstructure of Cognition Volume 1: Foundations.*** Cambridge, Massachusetts: MIT Press.

Rumelhart, D. E. & McClelland, J. L. (1995a). ***Parallel Distributed Processing – Explorations in the Microstructure of Cognition Volume 1: Foundations.*** Cambridge, Massachusetts: MIT Press.

Rumelhart, D. E. & McClelland, J. L. (1995b). ***Parallel Distributed Processing – Explorations in the Microstructure of Cognition Volume 2: Psychological and Biological Models.*** Cambridge, Massachusetts: MIT Press.

Sage, A.P. (Ed.). (1990). ***Concise Encyclopedia of Information Processing in Systems and Organizations.*** New York: Pergamon.

Sarle, W. S. (Ed.). (2004). ***Neural Network FAQ, part 1 of 7: Introduction.*** Periodic postings to the Usenet newsgroup comp.ai.neural-nets. Retrieved February, 9, 2004 form the World Wide Web: ftp://ftp.sas.com/pub/neural/FAQ.html

Schneider, W. (1987). Connectionism: is it a paradigm shift for Psychology? ***Behavior Research Methods, Instuments, & Computers,*** (19), 73-83.

Sharples, M. et al. (1994). ***Computers and Thought – A Practical Introduction to Artificial Intelligence.*** London: MIT Press.

Smith, K.A. (1999). ***Introduction to Neural Networks and Data mining for Business applications.*** South Melbourne, Australia: Corporate Printers.

Solso, R. L. (1991). ***Cognitive Psychology – Third Edition.*** Boston: Allyn and Bacon.

Stein, D. J. & Ludic, J. (Ed.). (1998). ***Neural Networks and Psychopathology: Connectionist models in practice and research.*** United Kingdom: Cambridge University Press.

Stubbs, D. (1988). Neurocomputers, M. D. ***Computing,*** (5), 14-24.

Sulloway, F.I. (1984). ***Freud, Biologist of the Mind.*** New York: Basic Books.

Tank, D. W. & Hopfield, J. J. (1987). Collective Computation in Neuronlike Circuits. ***Scientific American,*** (257), 104-114.

Taylor, W. K. (1956). Cortico-thalamic organization and memory. ***Proceedings of the Royal Society of London, Series B,*** (159), 466-478.

Todd, P. M. & Loy, D. G. (Eds.). (1991). ***Music and Connectionism.*** Cambridge, Massachusetts: The MIT Press.

Uttley, A. M. (1956). A Theory of the mechanism of learning based on the computation of conditional probabilities. ***Proceedings of the First International Conference on Cybernetics.*** Paris: Naumur, Gauthier-Villars.

Von Eckardt, B. (1993). ***What is Cognitive Science?*** Cambridge, Mass: MIT Press.

Warner, B. & Misra, M. (1996). Understanding Neural Networks as Statistical Tools. ***The American Statistician,*** (50/4), 284-293.

Wasserman, P. D. (1989). ***Neural Computing.*** New York: Van Nostrand Reinhold.

CHAPTER 3: MUSICAL NETWORKS

…whenever you want to synthesize a behavior for which you can more easily provide examples than algorithmic prescriptions, think about training a neural network to do the job for you (Dolson, 1991:16).

The caption of this section, along with the main title of the thesis, is obtained from *Musical Networks – Parallel Distributed Perception and Performance* – a 1999 publication by Griffith & Todd. In the author's opinion, the latter – in combination with its precursor *Music and Connectionism* (Todd & Loy, 1991) – accomplished invaluable pioneering groundwork in the application of artificial neural networks in music research. Both of these texts manifested as standard academically acclaimed texts on the topic. The publications also serve as imposing reviews of research conducted in this decidedly specialised dissection of study within the field of music over the past two decades. The introductory section mainly incorporates these texts together with selected writings from Marsden & Pople's *Computer Representations and Models in Music* (1992).

3.1 INTRODUCTION TO MUSICAL NETWORKS

According to Griffith & Todd (1999), Rumelhart and McClelland initially introduced parallel distributed processing (ANN computer models) in 1986 as a new set of computational tools to assist in the conception of the methods by which we make and listen to music. This statement is a vastly one-dimensional account of the manifestation of the exploitation of artificial neural networks in the Social Sciences,[28] of which the study of music forms a part. Even so, it is acceptable to say that the application of ANNs to music is a very recent phenomenon that originated in the late 1980s - following after an extended tradition of research conducted by scholars from diverse fields over many decades.

[28] The reader is referred to chapter 2 for a more comprehensive review in this regard.

Musical problems typically included in this new field of study were the processes and representations involved in music perception, production, comprehension and composition. More specifically, the musical themes dealt with in Todd & Loy (1991) include the categorization of chords and tones, perception of pitch, fingering of stringed instruments, computerized composition of melodies, and the aesthetic inferences thereof. Griffith & Todd (1999) also incorporated topics covering an extended range of musical activities, ranging from the perception of tonality, pitch, meter and rhythm, musical memory, the assimilation of melodic structure, and innovative methods fundamental to harmonization and composition.

The above-mentioned authors assumed that these processes were implemented in cognitive and perceptual mechanisms, operating on different representations of music in the human brain and body. Researchers in this field designed computer models based on *brain-style computation* to determine the possibility of encapsulating human musical behaviour in an artificial system. These models all employed certain types of parallel distribution processing, based on the method describing the way in which multitudes of interconnected neurons in the brain process information. These artificial neural network computer representations allocated the exploration of processes (such as learning and generalization), as well as forms of representations that were problematic or unfeasible to examine in former psychological models.

3.2 ARTIFICIAL NEURAL NETWORKS IN MUSIC RESEARCH

3.2.1 Historical perspective: symbolic AI systems versus musical networks

According to Leman (1992:267), the application of *intelligent computer systems* to music research is accounted for in the perception of music as a multifaceted construct existing on a number of levels, progressing from *acoustical signals* to *conceptual structures* and *compositional systems*. Various authors share this viewpoint regarding music, including Griffith & Todd (1999); Todd & Loy (1991); Georgescu & Georgescu (1990); Witten & Conklin (1990); Apostel, Sabbe & Vandamme (1986) and Broeckx (1981).

In the past, scholars have revealed a great deal of interest in the organizational features of –, and limitations that constitute these various dimensions of musical experiences. They gained valuable insights by examining this phenomenon from a number of perspectives – including Physiology, acoustics, psychoacoustics, music theory, Semiotics, Psychology, and Sociology. In addition to these, computer technologies have frequently been employed in the domain of music – proving to be successful in areas like composition, production and generation; also to a certain degree in analysis.

The 1950s witnessed the first employment of computers to model aspects of musical behaviour (Loy, 1991 & Camilleri, 1992). In a paper that discussed different approaches to the representation of musical knowledge within the computational paradigm, Camilleri (1992) provided what can now– in retrospect – be recognized as an historical overview to the development of a computational theory of musical cognition. In this article that was published more than a decade ago, Camilleri (1988) claimed that computer modelling in music might be thought of as a novel approach that could possibly unite different methodological aspects which have occurred through the juxtapositioning of an exhaustive musical theory[29] with other fields in the natural- and Social Sciences. His justification for the reason why an all-inclusive theory of music should be of a computational nature was that computation was the paramount way to develop, as well as to test a systematic general theory that connects music theory with the theory of musical cognition. In this paper, he explored the application of computers in music research by identifying four potentially non-exclusive approaches in use at that time (Camilleri, 1992:173-174):

- representation of musical data by grammars (*hierarchical levels and rule-based systems*);
- modular musical models (partial decomposability of processing and *data encapsulating*[30]);
- systems built on AI methodologies (*production systems; frame structures; expert systems*);
- systems based on cognitive data and connectionist models (*connectionist architecture and the modelling of specific attributes of music structure based on cognitive information).*

This discussion will focus exclusively on the last two approaches. For a comprehensive review of the remaining categories, the reader is referred to the article at hand.

In chapter 2, symbolic AI systems and ANNs were compared as distinctive models of human cognition.[31] This distinction is also applicable to the domain of music research, where (amongst other methodological approaches), symbolic rule-based systems that emerged from the tradition of AI were formerly employed and succeeded by connectionist systems like ANNs as models of musical cognition.

---

[29] Camilleri states that the computational paradigm allows for the inclusion of music *analysis, -theory* and *cognition* in an *overall* theory of music (Camilleri, 1992:171).

[30] The assumption that at particular stages of processing, certain representations are computed in the absence of additional information (Camilleri, 1988).

[31] Refer to section 2.3.1

Todd & Loy (1991: ix) gave the following description of connectionist systems made applicable to music research:

> *Connectionist systems employ "brain-style" computation, capitalizing on the emergent power of a large collection of individually simple interconnected processors operating and co-operating in a parallel distributed fashion. Models of many aspects of musical behavior require the learning, constraint satisfaction, feature abstraction, and intelligent generalization properties that connectionist approaches embody, at the same time demanding further advancement of these techniques.*

To be fair, it should be made apparent that the conscious preference of this dissertation is on the side of connectionism. Nevertheless, there are several more inclusive and objective comparisons between these two schools of thought, than allowed for in at this stage. A statement by Wasserman represents one example:

> *The field of Artificial Intelligence has been dominated in recent years by the logical- and symbol-manipulation disciplines. For example, expert systems have been widely acclaimed and have achieved many notable successes – as well as many failures. Some say that artificial neural networks will replace current Artificial Intelligence, but there are many indications that the two will coexist and be combined into systems in which each technique performs the task for which it is best suited* (Wasserman,1989:8).

In addition to this, the reader can consult Arbib (2003), Barnden & Chady (2003), Eysenck & Keane (2000), Haykin (1999), and Wasserman (1989) for an introduction and general overview to these two contrasting methodologies. Moutinho et al. (1994) provides a business-related consideration, and Balaban (1989), Ebcioğlu (1987) & Laske (1992) present an outline pertinent to Musicology. Smoliar (1994) also provides an objective comparison of these paradigms applied to a study of musical perception.

Human intelligence, from an AI point of view, was considered able to be depicted by a rule-based symbolic system, functioning with a memory in the form of a collection of *symbol manipulation rules.*[32] All the information contained in the system is overtly depicted in the form of stored data (*declarative knowledge*) that can be recovered and manipulated by rules (*procedural knowledge*), to form structures that represent knowledge of a specified area. To make this description pertinent to music, a simple example based on that of Leman[33] (1992:269) is given, explaining how the C-major chord would be stored in such a system:-

---

[32] Refer to Sharples et al. (1994:1, 21); Camilleri (1992:177) & Leman (1992:269).

[33] All the references to Leman in this section are cited from the article *Artificial Neural Networks in Music Research* (Leman, 1992: 265-301).

In the human memory system, the C-major chord is stored as the structure C-E-G (declarative knowledge). The information about how the data should be processed (procedural knowledge) is more unanimous - in this case it will be the rule describing how to create a C-major chord by adding a major- and minor third consecutively beginning with the note C. This rule could be generalized to construct any major triad from a single root note.

In the past, symbolic AI systems based on the described procedure have been successfully utilized by numerous scholars in an extended range of musical applications. Selected examples include the application of these methodologies in *harmonic analysis* (Maxwell, 1988 & Ebcioglu, 1988); as *models of listening* in Cognitive Systematic Musicology (Laske, 1987); as *expert* (symbolic, rule-based-) *systems* for composing (Ebcioglu, 1987), and as simple *architectures for music systems* (Balaban, 1989). However, these AI systems have been proven to be rather limited in their scope of application, usually being confined to score-based music.

In closing, it should again be accentuated that the association between AI and music indeed provided invaluable groundwork that paved the way for successive research in e.g. the field of connectionism. The contributions of AI towards the modeling of musical cognition have been sufficiently recognized by many scholars – one example being that of Balaban (1989). This author claimed that explorations in the domain of Cognitive Systematic Musicology, which were directed towards the symbiotic relationship between AI and music, were of consequence to both of these fields. She also stated that AI methodologies supplied music-based research with a descriptive power and litheness, qualities that were absent in previous numerical and grammatical models.

3.2.2 Music and Connectionism

Leman (1992) claimed that the challenge of computer-orientated music research was aimed towards the advancement from the score-based symbolic system paradigm to an approach instigated by the process of the physical manifestation of intelligent behaviour in the organization and operation of the human brain. He declared - in accordance with the arguments of Todd & Loy (1991) - that the connectionist[34] approach was an appropriate alternative to the symbolic programming methodologies of traditional AI. To endorse this assertion, a citation from Loy (1991:31):

> *…a connectionist network model can simultaneously memorize and generalize, these being two key elements in learning. Perhaps connectionism can show the way to techniques that do not have the liabilities of strictly formal systems.*

[34] The connectionist approach is also identified by Leman as the *subsymbolic* or *dynamic-systems-* approach (Leman, 1992:269).

In contrast to the rule-based symbol-processing approach, connectionism strives to realise cognitive performance by examining processing in neuron-like computing systems. As it is found on a vast parallel-processing paradigm, connectionism provided a methodological change from symbolic rule-based systems to a method based on dynamic systems – ANNs being one example of such a system.[35]

In 1992, Leman argued (in an entry entitled *Artificial Neural Networks in Music Research*[36]) that computer-based music research should have a firm connection with an awareness of the limitations which delineate the hierarchical and interconnected dimensions of musical phenomena. In his opinion, this could only be scientifically accomplished by employing intelligent devices that merge the litheness and preciseness of humanoid processing in areas such as *pattern recognition, intelligent association, abstraction, generalization, problem solving* and *access- and retrieval of information,* with a familiarity about the constraints marked out by the specified *semiotic level.*[37] Adding to this, he stated that certain preconceptions regarding the interaction of man with machine should be considered in order to deal with human characteristics in interactive communication. Following this, he encapsulated the demand for computer resources for music research in two questions that relate to the possibility of attaining artificially intelligent systems:

- *What is human intelligence? This century-old question relates to the types of cognitive and neural processes that are utilized during musical content processing like perception, composition and analysis.*
- *What kind of functional architecture and processing is required for the implementation of artificially intelligent manipulation of musical information? This relates to the specific type of knowledge-based system that is required, how information is obtained, retrieved, stored and manipulated.*

Leman supported the connectionist approach in this regard, in accordance with various other scholars, including Todd & Loy, (1991:39) who made the following statements the year before:

> *Connectionist models are finding increasing use in many domains within Psychology and Cognitive Science. Their ability to learn and store information, satisfy multiple constraints simultaneously, categorize stimuli, abstract features, create new representations, and generalize to novel inputs in ways akin to human and animal behavior makes these systems particularly attractive for modelling a variety of phenomena. Music perception and cognition require this same set of abilities, and so it is not surprising that connectionist models are well suited to capturing aspects of musical behavior as well.*

The argument for connectionist models was further supported by Dolson (1991:12), who claimed that artificial neural networks present an alternative to conventional AI and symbolic programming approaches in attaining advanced automated musical behaviour. These expectations and assumptions

---

35 *Classifier systems, genetic algorithms* and ANNs are encapsulated in the connectionist paradigm (Beltratti et al., 1996:72).

36 Published in *Computer Representations and Models in Music* (Marsden & Pople, 1992).

37 The semiotics of music is defined by Leman (1992: 268) as the *study of form-bearing elements.*

made more than a decade before indeed proved to be true – musical networks as connectionist models indeed succeeded to a great extent in many areas of music research where various conventional models had failed before.

3.3 MUSICAL NETWORKS: CONCEPTS OF UNIVERSAL SIGNIFICANCE

The outline on network architecture in Chapter 2 served as a brief introduction to a few significant features of generally encountered networks. This section will elaborate on the preface by discussing the concepts mentioned before more comprehensively and in reference to the field of music research. Before proceeding to a discussion of the architectures typically chosen for musical networks, it would be appropriate to elaborate on a few theoretical constructs of shared importance to ANNs in general and as applied to musical knowledge representation. Garson's (1998:36) abstract of a generic algorithm for ANN learning serves as a good overall introduction to these concepts:

> *A network composed of neurons (nodes) grouped in layers is constructed and connections between neurons are identified. Connection weights are initialized, usually to small random values. For i=1 to n training patterns, the i-th pattern is presented to the input layer. The weighted input is fed to the hidden layer. The activation levels of hidden layer nodes are calculated. When activation exceeds the threshold value, the neuron fires using a sigmoid or other activation (transfer) function. Patterns are fed through the network, looping until a minimum error stopping criterion is met or the network fails to stabilize. If training does not fail, the trained network is used to classify, predict or otherwise make inferences regarding data sets other than the training data set.*

In the following section, the author will build on Garson's synopsis by discussing the portrayal of data in an ANN, activation functions and backpropagation. In the course of the discussion the basic academically acknowledged ANN jargon[38] will be explained.

3.3.1 Artificial neural networks and knowledge representation

Fischler & Firschein (as cited in Haykin, 1999:23) describe knowledge as referring to the stored information or models used by a human or machine to interpret, predict, and appropriately respond to the outside world. According to Haykin (1999:24), there are two important features of knowledge representation, namely which information is made apparent, and how this data is encoded to retrieve at a later stage. Concerning intelligent systems such as ANNs, a satisfactory solution is equivalent to the adequate representation of knowledge. This could potentially be a very difficult task to accomplish by incorporating an ANN, taking into consideration the many different possibilities of representation from the inputs to the internal network factors.

[38] These terms are italicised throughout the text.

Consequently, an imperative task that a neural network should be able to achieve, is to learn an archetype of the particular environment in which it exists. To realize its aimed at objective, the network should be able to preserve this model sufficiently consistent with the real world. According to Haykin(1999:24), knowledge of the world is two-fold. *Prior information* refers to the recognized world state as signified by known facts. The other kind of knowledge is *observations* or *measurements* of the environment, usually being rather imperfect in nature. These observations function as a database from which *examples* are taken for the training of the network. A *labelled* example consists of an input signal linked with a matching desired response, or the target output. Such a collection of input-output connections are called a collection of *training data* (*patterns/vectors*), or the *training sample*. An *unlabelled* example contains various manifestations of the input signal exclusively.

Haykin (1999:25) illustrates the processes of *learning* and *generalising* in ANNs by describing the implementation of a training sample to recognise handwritten digits.[39] This type of *pattern classification* (to establish if an input vector fits to a specified category or not) resembles one of the most basic, and historically earliest example of the application of ANNs (Fausett, 1994).

The input units used in this example are pictures (consisting of black or white pixels) of ten digits. The target output is the identity of the specific number, the image of which is given as the input to the network. The training sample contains an extended number of handwritten numbers (representing a real-world situation). The initial step in creating the ANN is to choose a suitable network architecture. In this example, the input layer must contain the same amount of source nodes as the pixels of the input images. The output layer contains a neuron (node) for every digit, hence ten neurons. Learning can now be accomplished by training the network on a subset of examples, using an appropriate algorithm. One of the greatest advantages of ANNs is that they are not only able to learn from examples, but also from a limited subdivision of all feasible examples. The solution they obtain can keep its validity even when presented with unfamiliar examples.

After the learning process, the recognition functionality of the trained network will be assessed – a process described as generalisation. This is achieved by feeding the network unfamiliar information in the form of unidentified input images and comparing these results with the real identities of the specified digit. In this example it becomes clear that real-life information is used in the development of

[39] A *digit* is defined in the *Oxford English Dictionary Online* as *each of the numerals below ten (originally counted on the fingers), expressed in the Arabic notation by one figure; any of the nine, or (including the cipher, 0) ten Arabic figures* (Simpson & Weiner, 2004).

an ANN, *with the data set being permitted to speak for itself*. ANNs can therefore accomplish the required information-processing task, as well as supply an implicit representation of their environment.

To make this simple example a bit more musicologically appealing, an illustration based on the handwritten digit recognition problem, is presented in the next section. The suggested hypothetical challenge is to design a neural network to distinguish between authentic Afrikaans folk tunes and folk songs inspired by other cultural groups in South Africa. To simplify the matter, the author has chosen to make a rather biased assumption in that the collection of Afrikaans folk songs as published in the *FAK Volksangbundel vir Suid-Afrika*[40] (Hartman et al., 1986), resembles an authentic and inclusive representation of this type of music; also that this publication has been proven as a valid and reliable source of such information. Accordingly, the publication will serve as the working *sample* for this particular example. A sample is selected from the entire group from which one wants to draw conclusions from (or the *population* as described by Babbie, 1998:109), in this case consisting of all possible traditional Afrikaans folk songs.

The input signals are songs from the FAK. These will probably be analysed in terms of constructs like tonality, harmony and rhythm – working from the score provided or electronically by using midi samples of these songs that are readily accessible from the Word Wide Web.[41] Clearly, the complexity of the network will be influenced by the quantity of attributes chosen. The target output is very simple, restricted to *yes* for belonging to the category of Afrikaans folk songs, or *no* for the contrary. The preferred network architecture is multi-layered with three layers, feedforward, and supervised, as illustrated in figure 3.1.[42] Although it is possible to choose many layers in neural network software, most applications work adequately with three to five layers in the network.

The next step is to train the network on a training sample containing a selection of songs from the FAK. The amount of input neurons will depend on the analyzed constructs of the input songs. Related to music, the fundamental constituent (a single neuron/ node/ unit) of the artificial network can represent an abundance of diverse constructs in the form of chunks of data encoded in the network. Examples include *frequencies*, *pitches*, *rhythmical* or *melodic fragments*, *filters* or various other types of attributes that could be functional in the system (Leman, 1992:271). Subsequently, a single neuron will

---

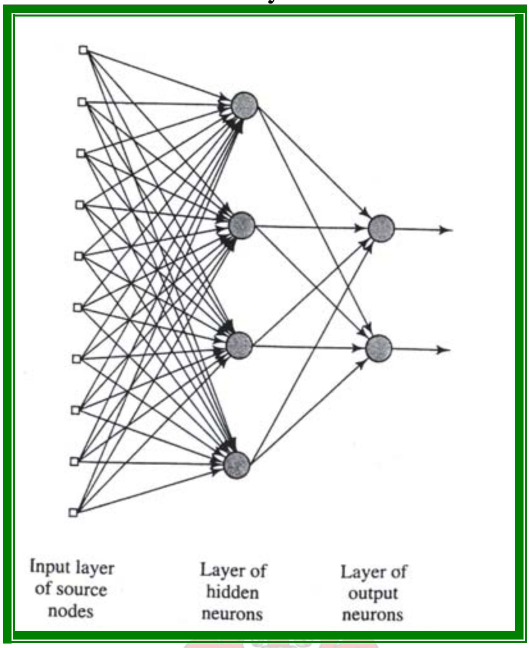
[40] This collection of traditional Afrikaans folk songs is published by the *Federasie van Afrikaanse Kultuurverenigings* (Federation of Afrikaans Culture Societies).

[41] <http://esl.ee.sun.ac.za/~lochner/blerkas/index.html>

[42] Cited from Haykin (1999:22). In this instance, the input layer is considered as an independent layer –therefore the model is described as a three-layered network.

be incorporated into a configuration representative of a specific concept, and it will only have meaning in accordance with the global pattern of neurons that characterizes this particular concept.

Fig. 3.1 Selected three-layered network architecture



The output layer contains two neurons, relating to the two categories of inclusiveness. The selected learning algorithm is backpropagation.[43] Following the learning process, the trained network's recognition performance (generalisation) will be tested. The network will be presented with songs not seen before and the results compared to those obtained in the learning phase.

To conclude this section on the depiction of stored information, Anderson (as cited in Haykin, 1999:25-29), stipulated four universal rules for knowledge representation in an ANN. For a comprehensive mathematical account of these rules, the reader can consult the identified source.

- *Similar inputs from similar classes should usually produce similar representations inside the network, and should therefore be classified as belonging to the same category.*
- *Items to be categorized as separate classes should be given widely different representations in the network.*
- *If a particular feature is important, then there should be a large number of neurons involved in the representation of that item in the network.*
- *Prior information and invariances should be built into the design of a neural network, thereby simplifying the network design by not having to learn them.*

[43] The specific choice of this learning rule will be validated and elucidated in section 3.2.3

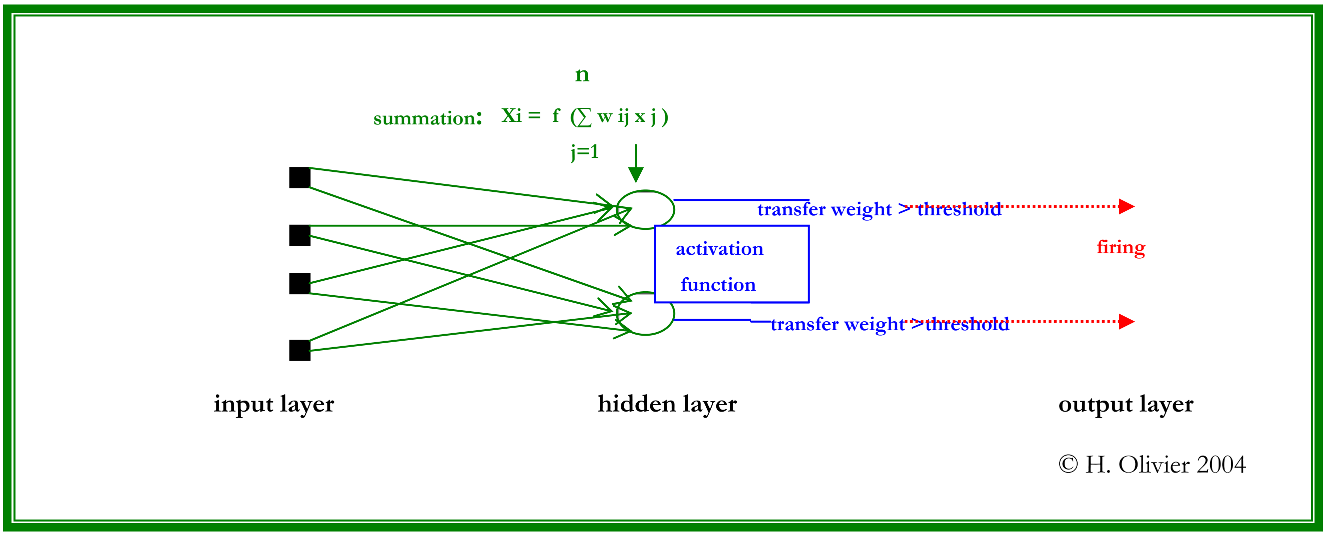
3.3.2 Activation functions

By this time it should be evident that the main issues in determining the behaviour of an artificial neuron amount to the pattern of weighted connections over which it sends and receives signals, the computation of the weighted input signal, and the application of an output function. The input layer involves the most straightforward computations by only generating the training sample. The output layer computes signals from the hidden layers and produces the weights that will be used for prediction. The middle or hidden layers are involved with more complex calculations – they recognise interdependencies in the network. As illustrated in figure 3.2, neurons in the hidden layer must calculate the weighted incoming signals (the *net input*) and send a corresponding signal to the output layer. As stated in chapter 2, this summation function is mathematically depicted by the following formula, where **Xi** symbolises the net input:

$$\mathbf{Xi} = f\left(\sum_{j=1}^{N} w_{ij}\, x_j\right)$$

In most networks all weights are aggregated, although there are a few exceptions where only fixed weights are calculated. Following summation, the weights are sent to the subsequent layer through a calculated output function, also referred to as the *activation function*, *transfer function,* or *squashing function* (Garson, 1998: 26, 31). The activation function regulates the allowed scope of the output signal and converts the summed weighted inputs to a transfer weight called the *activation value*. This value will determine if an output signal will be sent (*firing*) or not. Firing will only happen if the activation value is above a *threshold level* set by a *learning rule*. The threshold can be adjusted by including an additional signal (*input bias*) in the network.

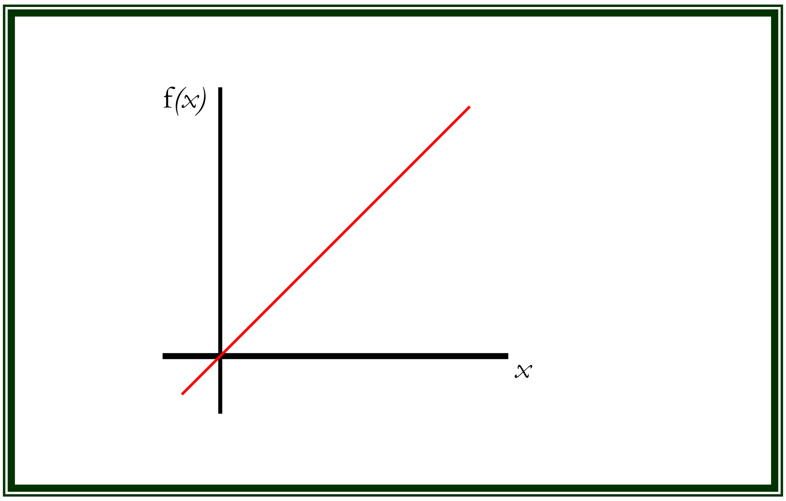
Fig. 3.2 Calculations of the hidden layer



To attain the complex computational abilities typical of multi-layer networks, non-linear activation functions should be used. The explanation for the usage of non-linear functions is that if you were to send a signal through two or more layers of elements with linear activation functions, the result will be the same as when using a single- layered network with its characteristically limited computational ability. Although there are many possible activation functions to choose from,[44] in most applications – including musical networks – only a few are typically encountered.

The first type of activation function which will be categorised is the *identity function* – the calculated activation function of the input units. Mathematically, the identity function is represented by the following formula: $f(x) = x$ ***for all*** x.

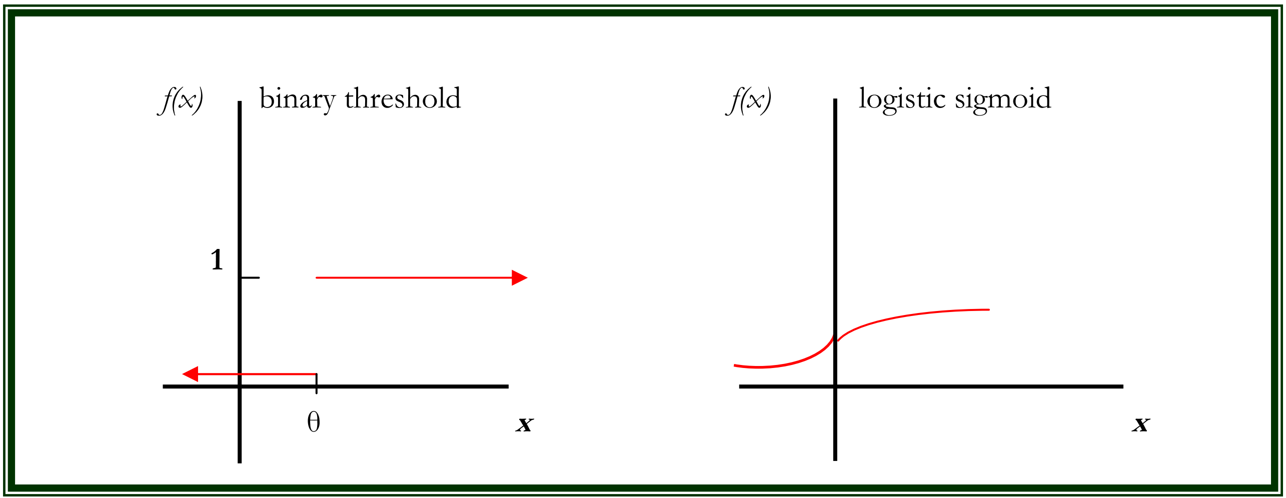
Fig. 3.3 Identity activation function



The *binary step* or *threshold* function is synonym with single-layered networks and converts the net input to a binary (1/0) or bipolar (1/-1) output: $f(x) = 1$ ***if*** $x \geq \theta$ ***or*** 0 ***if*** $x < \theta$. Multi-layered networks trained by backpropagation frequently employ sigmoid activation functions like the logistic function (with desired outputs from 0 to 1) and the hyperbolic tangent function (with desired outputs between 1 and -1). The sigmoid activation function is continuous, proliferates *monotonically* and takes on constant values as the input moves towards positive or negative infinity (Garson, 1998: 97). It keeps the network's output at 0 until a specified threshold level of inputs forces it on a progressively steep ascendant curve to an output of 1. The logistic sigmoid function can be scaled to have a suitable range of values – the *bipolar sigmoid* (1 to -1) is the most frequently encountered.

[44] The reader is referred to White (1989) for a description on various activation functions.

Fig. 3.4 Binary threshold function and logistic sigmoid function



As stated before, the firing of a neuron is dependent on a threshold level established by the specific learning rule chosen for the network. Fausett (1994:429) provides the most basic description of *training algorithms* or learning rules: *Procedures for modifying the weights on the connections links in a neural net.* Although there are a great selection of learning rules (e.g. the Hebbian-, Hopfield-, bipolar Hopfield- (also identified as the *brain-state-in-a-box-* rule), Adaline-, competitive learning-, delta- and cum delta learning rules), the backpropagation training algorithm is the most frequently encountered in musical- and other applications. This learning rule will also be employed in the applied part of this thesis. For these reasons, the following discussion will concentrate exclusively on backpropagation.

3.3.3 Backpropagation

In essence, the backpropagation algorithm is a method to set the weights of a multi-layered feedforward network. As mentioned in Chapter 2, backpropagation overcame the limitations of single-layered networks (perceptrons) by being able to solve problems that are not linearly separable.[45] The term for this learning algorithm was derived from its functionality in *propagating* the error between output layer predictions and authentic training sample values *backwards* through the connections to update the weights used by earlier layers (Garson, 1998:29).

Sometimes also referred to as the *generalized delta rule,*[46] backpropagation should not be mistaken for feedback or recurrent connections which take untainted outputs back to previous layers. It acts only in

[45] Refer to section 2.3.2.

[46] Fausett (1994: 289) & Smith (1999: 45).

a feedforward manner by sending data on error back to previous layers so that their functional calculations can be modified. Arbib (2003:21) describes backpropagation as an *adaptive architecture* that does not simply provide a basic rule for weight modification, but also considers the neuron's location in the network when specifying weight adjustments.

In a most basic description of its functionality, backpropagation decreases the total squared error of the network's calculated output by means of a gradient descent process. Similar to the majority of ANNs, the objective is to train the network to attain a balance between the ability to react accurately to the training sample (learning) and the capability of giving sufficient responses to unseen data (generalization). Three phases can be identified in the training of a backpropagation network. These involve the feedforward of the input training sample, the computation and backpropagation of the associated error, and finally the appropriate modification of the weights. After training, the network can be applied by utilising the computations of the feedforward phase only, thus a backpropagation network is capable of *rapid output generation* (Fausett, 1994:290).

Dolson (1991: 5-7) illustrates the key operations of the backpropagation learning rule through a simple musical example that will briefly be discussed. For a more comprehensive mathematical review of this learning rule the reader can consult Arbib (2003), Bishop (1999), Garson (1998), or Beltratti et al. (1996).

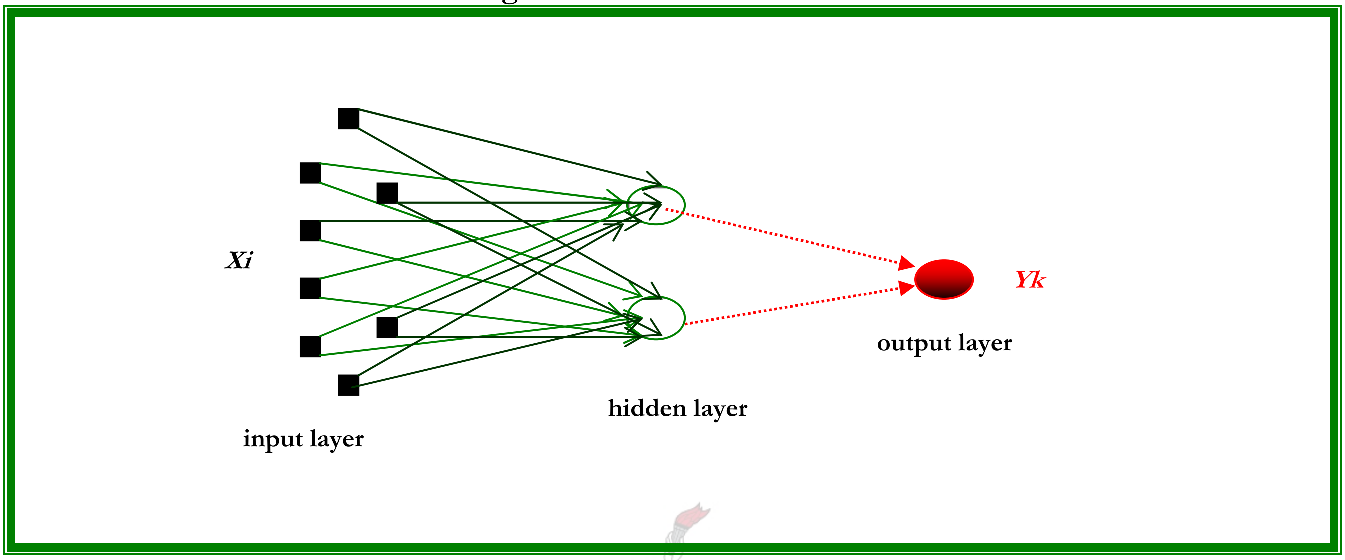
Dolson presents a scenario of training an ANN to mimic people's decisions about good or bad rhythms. If successful, such a musical network could be utilized as a *filter* for *automated composition*. In this instance, the network is trained on examples of what the test subjects have perceived as good or bad rhythms. Good and bad rhythms will be reliant on whether or not a note is accentuated, as well as on the presence of rests. The evaluation is based on a single measure of 4/4 –time. The shortest notes presented are eighth notes, therefore there will be eight possible rhythm-related input units of notes being either an attack (1.0) or a rest (-1,0). The output is defined as *human judgements of good or bad rhythms*, and can take the values of 1,0 (good rhythm) or –1,0 (bad rhythm).

The selected architecture for this simulation is a multi-layered, feedforward network with two hidden units, as illustrated in figure 3.5.[47] Dolson (1991) and Garson (1998) claim that there are no fixed rules to establish the amount of neurons in the hidden layer. Typically, a process of trial and error seems to

[47] The illustration is based on that of Dolson (1991:6).

be the solution in this regard, although there are some guidelines.[48] The network's computational power and generalization ability will be greater when using fewer units, therefore the choice of only two neurons in the hidden layer.

Fig. 3.5 Selected architecture



Having established the architecture, the network must now be trained by adjusting the weights so that the correct positive (1,0) or negative (-1,0) output is attained. For this purpose the backpropagation learning algorithm will be applied. To provide a very simple explanation of the rule, consider for a moment that all the weights have random values. It will be straightforward to compute the output function (*Yk*) of a given sequence of inputs (*Xi*). In addition, the training sample provides a set of given output functions for corresponding input patterns. By calculating the disparity between the actual output value and the desired value, an error for every output unit can be established. By adding the squares of all the discrete errors, a total error (ε) can be calculated:

$$\varepsilon = \sum_{k} (Yk - Tk)^2$$

The desired output (target values) that the network should learn to generate is depicted by (***Tk***).

To obtain the smallest possible amount of error, the weights should be fixed so that the network will generate the desired target outputs directly from given inputs. This can be done by repeatedly modifying (increasing or decreasing) the initial randomized weights until a very small error is found – in

[48] Garson (1998: 83-87) provides a few directives for choosing the amount of hidden layers.

other words *tracing the error impact backwards in the network* and finding an optimal set of weights. This process of modification is based on a very simple principle. If an output function is smaller than its desired target value, the weights to its current excitatory hidden units should be strengthened so as to yield a stronger connection. The opposite applies when weaker connections are needed.

As backpropagation is applied to a generally encountered architecture (multi-layered, feedforward and supervised), it has a very wide area of application extending over many fields, including music. Backpropagation is also the most commonly used learning paradigm for business applications of neural networks (Wong et al., as cited in Smith, 1999). In addition to these, many variations of this learning rule have been invented during the past few years, making its field of application even more diverse.

3.4 MUSICAL NETWORK ARCHITECTURE ARCHETYPES

Following a rather extensive exploratory review of the most recent -, as well as previously conducted applications of ANN in music research, the author has concluded that the majority of musical network architectures encountered are supervised feedforward networks, self-organising networks, and constraint-satisfaction networks. In the subsequent section these architectures will be discussed and a few examples of previously successful applications will be presented. The examples are chosen mainly on the basis of their relevance to the aimed at application of ANNs to advertisement music, which will be presented in chapter 5. In addition to this, a few additional examples are included to demonstrate the diversity of the application of ANNs in music research.

3.4.1 Supervised, feedforward networks

The fundamental nature of supervised, feedforward networks has already been described in previous sections.[49] This type of ANN is by far the most frequently encountered network in music research, as well as in business applications. Subsequently, a synopsis of studies that incorporated multi-layered feedforward supervised learning networks using the backpropagation algorithm is presented:-

- Todd (1988) investigated automated music composition by using a backpropagated musical network.

[49] Refer to sections 2.4, 3.1, and 3.3.

- In 1989 Sano & Jenkins applied this architecture in a pitch perception model, founded on principles related to the functioning of the human ear. Todd (1989) used the model as a training device to store a series of patterns.

- Bharucha & Olney (1989) used auto-associated networks[50] to learn octave equivalence and Western European- and Indian tonal schemas. They argued that ANNs can provide explicit hypotheses concerning the perception of music by individuals form different cultures.[51]

- Weigent, Huberman & Rumelhart (1990) demonstrated that this type of musical network can sufficiently predict samples from a *chaotic time series.*

- Bellgard & Tsang (1999) described *HARMONET*[52] – a harmonization system that combines neural network- and symbolic AI methodologies. The system has been fairly successfully used to harmonize chorales in the style of J. S. Bach.

- Hörnel & Menzel presented their results on *HARMONET* and *MELONET* in an article called *Learning Musical Structure and Style with Neural Networks in* 1998. These represent two types of feedforward ANN models that learn to identify and reproduce a certain musical style.

- The purpose of Casey's (1999) research was to prove that gestural information for sound models (related to the physical playing of a musical instrument), can be retrieved from audio signals. He demonstrated the successful usage of feedforward, backpropagation musical networks, as well as other forward models, to learn the mapping of sounds to these gestural parametric representations.

3.4.2 Self-organised ART networks (recurrent networks)

In essence, adaptive resonance is a theory of human cognitive information processing (Arbib, 2003: 87), mainly developed by Grossberg. The supposition evolved from research studies conducted in subjects such as *cortical development*, *vision, speech,* and *reinforcement learning.* Subsequently, adaptive resonance theory advanced into ANNs that can be applied as unsupervised or supervised learning models to problems such as pattern recognition and prediction. Grossberg (1976), Levine (2000), Carpenter & Grossberg (1992), and Kasuba (1993) - amongst others - made valuable theoretical contributions in this regard.

This type of ANN usually has a self-organizing, unsupervised architecture and use feedback from the environment and associative learning to solve classification problems. To recapture, associative learning

---

[50] Auto-associated networks have the same amount of input- and output neurons.

[51] These authors examined how people form one culture perceive the music of another.

[52] Lischka (1987) and Hild et al. (as cited in Griffith & Todd (1999)) also reported on the application of HARMONET.

occurs whenever the weights of two linked neurons with similar activities, are strengthened. ART-networks do not have any hidden layers and therefore display constrained generalization capacities. They are also susceptible to the sequence in which they are presented with data. However, they do achieve good results when applied to predominantly noise-free data sets. The following studies, which have effectively employed ART-musical networks, have been accomplished:-

- Williams & Zipser (1990) trained a temporary recurrent network to generate a sinusoidal oscillating output.

- Page was involved in a few studies that focussed on self-organising musical networks and published articles on this theme in 1991 and 1993.

- Gjerdingen (1991) used an ART-network to learn musically justifiable classes of complex patterns taken from musical sequences from Mozart.

- Taylor & Greenhough (1994) applied a supervised ART-network in a pattern recognition problem involving the identification of pitch, regardless of the type of instrument that produces the sound.

- Katz (1995) constructed a simple two-layered recurrent network to serve as a model of harmonic resolution, founded on the theory of affect. The looped resonance model consisted of a chord-recognition layer that feeds back to a note-recognition layer. Affect was measured by the amount of shared preservation of the competing neurons. Katz demonstrated the correspondence of the model to the rules of harmony, as well as its ability to predict dynamic and adaptive effects.

- Mozer (1999) trained a recurrent network, identified as *CONCERT,* on a training sample of existing melodies with the aim of the network composing original music.

3.4.3 Constraint-satisfaction networks

Barden & Chady (2003:114) identified *soft constraint satisfaction*[53] as one advantage that ANNs hold over symbolic AI. They described this as the possibility to arrange for some hypothesis to compete and cooperate with each other's levels of confidence until a stable set of hypotheses is found. Hypotheses are represented by neurons and constraints are encoded on the connections between them. This actually means that these networks are more responsive to subtle contextual effects since numerous data sources can be integrated to operate in parallel, and interact efficiently.

[53] The term *soft* infers that none of the constraints have to be complied with completely.

According to Leman (1992:279), constraint-satisfaction networks represent a major category of musical networks. The continuous Hopfield network, Boltzmann machine without learning, Gaussian machine and Cauchy machine all belong to this category of ANNs (Fausett, 1994:335). All the networks have fixed weights that integrate data regarding the constraints and the quantity to be optimized. By repetition they discover an accepted pattern of output signals that represent the answer to a given problem. Concerning music, the following selection of studies is included:-

- Bharucha & Olney (1989) argued that it is frequently advantageous to build an ANN, the connections of which are confined to established music-theoretic constraints. Such constraint-satisfaction models could then be used to study the operation of many constraints at the same time as well as provide the opportunity of examining redundancies in a theory of music. They commented on their experimentation with such a network. The aim of the musical network was to reveal the extent to which simple constraints of Western European harmony could explain more subtle and complex ones.

- In an article entitled *Pitch, Harmony, and Neural Nets: A Psychological Perspective*, Bharucha (1991) describes a constraint-satisfaction musical network called *MUSCAT* that learns to find chords and keys from tones.

- In 1992 Scarborough, Miller & Jones demonstrated *BEATNET* – a constraint satisfaction model applied to metre perception problems.

- Bellgard & Tsang (1999) published an article that explains how to teach a completion-based constraint satisfaction network to learn symbolic rules of music harmonization. The system (called an *effective Boltzmann machine)* was subsequently used to harmonize unfamiliar melodies.

In chapter 5, a hypothetical scenario of a musical network applied to research on South African advertisement music will be presented. The architecture of the assumed network will be supervised and feedforward, and the backpropagation algorithm will be used as the learning rule. The foundation of the scenario will be centred on the research questions that were presented in the introduction to the thesis. The objective of this exercise is to determine the possibility of applying results from diverse theoretical analyses to a musical technological context. The possibility of creating this computer-based resource tool – which could serve as an aid to people working in the advertising industry – will then be examined and assessed.

The next chapter will function as an introduction to this applied part, by providing the necessary theoretical foundation to the aimed at experiment.

References

Apostel, L., Sabbe, H. & Vandamme, F. (Eds). (1986). Reason, emotion and music: towards a common structure for arts, sciences and philosophies based on a conceptual framework for the description of music. ***Communication & Cognition.*** Ghent: Unknown.

Arbib, M. A. (2003). (ed.). ***The Handbook of Brain Theory and Neural Networks.*** Cambridge, Massachusetts: The MIT Press.

Babbie, E. (1998). ***The Practice of social Research.*** Wadsworth Publishing Company: Johannesburg.

Balaban, M. (1989). The cross fertilization relationship between music and AI. ***Interface,*** (18), 89-115.

Barnden, J. A. & Chady, M. (2003). Artificial Intelligence and Neural Networks. In Arbib, M. A. (Ed.). ***The Handbook of Brain Theory and Neural Networks,*** (113-117). Cambridge, Massachusetts: The MIT Press.

Bellgard, M. I. & Tsang, C. P. (1999). Harmonizing Music the Boltzmann Way. In Griffith, N. & Todd, P. M. (Eds). ***Musical Networks- Parallel Distributed Perception and Performance,*** (261-277). Cambridge, Massachusetts: MIT Press.

Beltratti, A, Margarita, S. & Terna, P. (1996). ***Neural Networks for Economic and Financial Modelling.*** London: International Thompson Computer Press.

Bharucha, J. J. (1991). Pitch, Harmony, and Neural Nets: A Psychological Perspective. In Todd, P. M. & Loy, D. G. (Eds). (1991). ***Music and Connectionism,*** (84-99). Cambridge, Massachusetts: MIT Press.

Bharucha, J. J. & Olney, K. L. (1989). Tonal cognition, Artificial Intelligence and neural nets. ***Contemporary Music Review,*** (4), 341-356.

Bishop, C. M. (1999). ***Neural Networks for Pattern Recognition.*** Oxford: Oxford University Press.

Broeckx, J. L. (1981). ***Muziek, ratio en affect.*** Antwerpen: Metropolis.

Casey, M. A. (1999). Understanding Musical Sound with Forward Models and Physical Models. In Griffith, N. & Todd, P. M. (Eds). ***Musical Networks- Parallel Distributed Perception and Performance,*** (45-61) Cambridge, Massachusetts: MIT Press.

Camilleri, L. (1988). A Modular Approach to Music Cognition. ***Interface,*** (18), 33-44.

Camilleri, L. (1992). Computational Theories of Music – theoretical and applicative issues. In Marsden, A. & Pople, A. (Eds). ***Computer Representations and Models in Music*** (171-185). London: Academic Press.

Carpenter, G. A. & Grossberg, S. (1992). A self-organizing neural network for supervised learning, recognition, and prediction. ***IEEE Communications Magazine,*** (30/9), 38-50.

Dolson, M. (1991). Machine Tongues XII: Neural Networks. In Todd, P. M. & Loy, D. G. (Eds). ***Music and Connectionism*** (3-15)***.*** Cambridge, Massachusetts: MIT Press.

Ebcioğlu, K. (1987). Report on the CHORAL project: an expert system for harmonizing four-part chorales. ***Report RC 12628.*** Yorktown Heights: IBM, Thomas J. Watson Research Center.

EB.C.ioglu, K. (1988). An expert system for harmonizing four-part chorales. ***Computer music Journal,*** (12/13), 43-51.

Eysenck, M.W. & Keane, M.T. (2000). ***Cognitive Psychology: A student's handbook*** (4th edition). Hove: Erlbaum.

Fausett, L. (1994). ***Fundamentals of Neural Networks.*** New Jersey: Prentice-Hall, Inc.

Garson, G. D. (1998). ***Neural Networks: An Introductory Guide for Social Scientists.*** London: SAGE Publications.

Georgescu, C. & Georgescu, M. A. (1990). A system approach to music. ***Interface,*** (19), 15-52.

Gjerdingen, R. O. (1991). Using Connectionist Models to Explore Complex Musical Patterns. In Todd, P. M. & Loy, D. G. (Eds). ***Music and Connectionism*** (138-149). Cambridge, Massachusetts: MIT Press.

Griffith, N. & Todd, P. M. (Eds). (1999). ***Musical Networks: Parallel Distributed Perception and Performance.*** Cambridge, Massachusetts: MIT Press.

Grossberg, S. (1976). Adaptive pattern classification and universal recoding: I. Parallel development and coding of neural feature detectors. ***BIOL. Cybern.,*** (23), 121-134.

Hartman, A. C. et al. (Eds.). (1986). ***Die FAK Volksangbundel vir Suid-Afrika.*** Cape Town: Protea Boekhuis.

Haykin, S. (1999). ***Neural Networks- a comprehensive foundation***. USA: Prentice-Hall, Inc.

Hörnel, D. & Menzel, W. (1998). Learning Musical Structure and Style with Neural Networks. ***Computer Music Journal,*** (22/4), 44-62.

Katz, B. F. (1995). Harmonic Resolution, Neural Resonance, and Positive Affect. ***Music Perception,*** (13/1), 79-108.

Kasuba, T. (1993). Simplified fuzzy ARTMAP. ***AI Expert,*** (8), 18-25.

Laske, O. (1987). Can we formalize and program musical knowledge? An inquiry into the focus and scope of cognitive Musicology. ***Musicometrika,*** (1), 257-280.

Leman, M. (1992). Artificial Neural Networks in Music Research. In Marsden, A. & Pople, A. (Eds). ***Computer Representations and Models in Music*** (265-301)***.*** London: Academic Press.

Levine, D. S. (2000). ***Introduction to Neural and Cognitive Modeling.*** Mahwah, New Jersey: Erlbaum.

Lischka, C. (1987). Connectionist modeling of musical thinking. In ***Proceedings of the 13th International Computer Music Conference,*** (190-196)***.*** San Fransisco: Computer Music Association.

Loy, D. G. (1991). Connectionism and Musiconomy. In Todd, P. M. & Loy, D. G. (Eds). ***Music and Connectionism*** (20-36)***.*** Cambridge, Massachusetts: MIT Press.

Marsden, A. & Pople, A. (Eds). (1992). ***Computer Representations and Models in Music.*** London: Academic Press.

Maxwell, H. J. (1988). An expert system for harmonic analysis of tonal music. ***Proceedings of the First Workshop on AI and Music,*** (Mineapolis, St. Paul),(AAAI-88), 20-33.

Moutinho, L., Curry, B., Davies, F. & Rita, P. (1994). ***Computer Modelling and Expert Systems in Marketing.*** London: Routledge.

Mozer, M. C. (1999). Neural Network Music Composition by Prediction: Exploring the Benefits of Psychoacoustic Constraints and Multi-scale Processing. In Griffith, N. & Todd, P. M. (Eds). ***Musical Networks- Parallel Distributed Perception and Performance,*** (227-260). Cambridge, Massachusetts: MIT Press.

Page, M. (1991). The musical expectations of self-organising neural networks. In Alphonce, B. & Pennycock, B. (Eds.). ***Proceedings of the 1991 International Computer Music Conference,*** (206-209). San Francisco: International computer Music Association.

Page, M. (1993). ***Modeling Aspects of Music Perception Using Self-Organizing Neural Networks.*** Unpublished doctoral thesis, University of Wales, College of Cardiff, Dept. of Physics.

Rumelhart, D. E. & McClelland, J. L. (Eds.). (1986). ***Parallel distributed Processing- Explorations in the Microstructure of Cognition.*** Cambridge, Massachusetts: MIT Press.

Sano, H. & Jenkins, B. K. (1989). A neural network model for pitch perception. ***Computer Music Journal,*** (13), 41-48.

Scarborough, D. L., Miller, P. & Jones, J. A. (1992). On the perception of meter. In Balaban, M. EB.C.ioglu, K. & Laske, O. (Eds.). ***Understanding Music with AI: Perspectives in Music Cognition,*** (427-447), Cambridge, MA: MIT Press.

Sharples, M. et al. (1994). ***Computers and Thought – A Practical Introduction to Artificial Intelligence.*** London: MIT Press.

Simpson, J. A. & Weiner, E. S. C. (Eds.). (2004). Digit, *n.* ***Oxford English Dictionary Online,*** Draft Mar. 2000. Oxford University Press: retrieved at http://dictionary.oed.com/cgi/entry/00299451, 14 February 2004.

Smith, K.A. (1999). ***Introduction to Neural Networks and Data mining for Business applications***. South Melbourne, Australia: Corporate Printers.

Smoliar, S. W. (1994). Modelling Musical Perception: A Critical View. ***Connection Science,*** (6), 209-222.

Taylor, I. & Greenhough, M. (1994). Modelling Pitch Perception with Adaptive Resonance Theory Artificial Neural Networks. ***Connection Science,*** (6), 135-154.

Todd, P. M. (1988). A Sequential Network Design for Musical Applications. In ***Proceedings of the 1988 Connectionist Models summer school.*** San Mateo, California: Morgan Kaufmann, Publishers.

Todd, P. M. (1989). A connectionist approach to algorithmic composition. ***Computer Music Journal,*** (13), 27-43.

Todd, P. M. & Loy, D. G. (Eds.). (1991). ***Music and Connectionism.*** Cambridge, Massachusetts: MIT Press.

Wasserman, P. D. (1989). ***Neural Computing.*** New York: Van Nostrand Reinhold.

Weigent, A., Huberman, B. & Rumelhart, D. E. (1990). Predicting the Future: A connectionist Approach. ***Technical Report PDP-90-01.*** Stanford: Stanford University, PDP Research Group, Department of Psychology.

White, H. (1989). Neural-network learning and statistics. ***AI Expert,*** (4/12), 48-52.

Williams, R. J. & Zipser, D. (1989). A Learning algorithm for Continually Running Fully Recurrent Neural Networks. ***Neural Computation,*** (1), 270-280.

Witten, I. & Conklin, D. (1990). Modeling music: systems, structures, and prediction. ***Interface,*** (19), 53-66.

CHAPTER 4: LITERATURE REVIEW AND SOME METHODOLOGICAL CONSIDERATIONS

This chapter serves as the theoretical foundation of the musical network simulation, which will be presented in chapter 5. To set the ground for such an endeavour, the present chapter is structured in the following way:

It commences with a chronologically organized interdisciplinary literature review of studies conducted in the fields of Psychology of Music, Cognitive Science and Consumer Science. Research done in the fields of Cognitive Psychology, Neuropsychology, and Cognitive Systematic Musicology is grouped under Cognitive Science, as validated in chapter 1.[54] It is the author's belief that by assimilating such an ensemble of fairly diverse fields from the social- as well as the natural sciences, the functionality and applicability of the presumed musical network could potentially be rather comprehensive. Following the literature review, a few important methodological considerations will be discussed. This will be in relation to the application of ANNs in a predominantly social scientific situation, such as research on the affective reactivity to advertisement music.

4.1 LITERATURE REVIEW

As asserted in the introduction, the thesis investigates the subject of advertisement music from a multidisciplinary point of view. For this reason, this literary inquiry includes reviews from the fields of Psychology– and Social Psychology of Music, Cognitive Science and Consumer Science. The various research projects are chosen on the basis of their potential applicability to the research questions. Potential shortcomings of these studies will be identified throughout the review. Note that this section

[54] Refer to figure 1.1.

is based on the first chapter and should be read in conjunction with theoretical findings as presented in that section.

4.1.1 Psychology- and Social Psychology of Music

As established in Chapter 1, these disciplines have made substantial theoretical contributions regarding the understanding of affective processes underlying musical experiences. Before presenting a synopsis of studies that had been done in these fields, a few comments on their ecological validity are in order.

The various research inquiries constitute a combination of studies using music from either an existing repertoire set in a definite musical context (mostly Western classical) as stimuli, or otherwise short sound sequences disconnected from any musical context. According to Gabrielsson & Lindström (2001), although the employment of contextual music when examining emotional expression in music insures ecological validity, inferences about the effects of discrete structural factors are perplexing and do not possess a lasting significance. On the other hand, studies incorporating musical fragments where the structural factors are systematically changed, are only ecologically valid to a certain degree. However, these give room for more explicit deductions about distinct structural factors. Hence, employing the two approaches in parallel or in combination – as applied in this review – represents a better methodology.

- In a very early study, Gundlach (1935) examined people's perceptions of composers' expression of mood or attitude. He tested subjects on different phrases from the Western classical repertoire and concluded that the speed of music was most directly associated with perceived expression. Other significant factors (in order of importance) included rhythm, interval allocation, orchestral range, loudness, average pitch, and melodic scope.
- As stated in chapter 1, scholars of music have been systematically studying the correlation between music and human moods for a very long time. For a considerable period, research had been focused on the construction of lists of adjectives to identify the affective states in musical sequences – typically being derived from self-reports by test subjects. Publications of this nature include those of Hevner (1936), Farnsworth (1954), and Wedin (1972), to name but a few examples from an extensive collection. More contemporary studies, aimed at the identification of affective states in relation to music, incorporated alternative research methods like semantic differentiation and the correlation of musical mood with colours, visual forms, dance movements and finger-tip pressure (Giomo, 1993).

- In *The Language of Music*, Cooke (1990) maintains that it is attainable to create a database of the expressive gestures of music's vocabulary. He specifies the array of elements of musical expression as a system of tonal tensions, which can be understood melodically as well as harmonically. He also claims that there exists a natural association between musical figures and feeling, and that these musical gestures are legitimate for all time, set apart from any social and historical context.

- Thompson & Robitaille (1992) exposed subjects to original compositions, asking the composers to depict sorrow, joy, dullness, excitement, anger and peace in monophonic accompanied melodies. In general, the subjects observed the aimed at expressions. An analysis of the scores illustrated the following: sad melodies were generally slow with minor or chromatic harmonies; cheerful melodies were pronounced tonal and demonstrated rhythmical diversity. Melodies perceived as exciting were fast with high pitches and interval jumps; tedious ones were gradual tonal. Irate melodies were typically atonal or chromatic and demonstrated intricate rhythmical qualities, whereas placid ones were slow and tonal with stepwise movement dissolving into melodic leaps.

- Daoussis, McKelvie, Glasgrow, Cartier, Wilson and Dollinger (in Dollinger, 1993: 73) found that the *musical preferences* of individuals correlated with their *personality traits*. Their empirical studies proved a differentiation in the musical preferences of extrovert- versus introvert personalities and conservatives versus liberals. The results confirmed the prediction that openness to experience is positively related to enjoyment of a variety of musical styles. It further suggested that persons scoring high on neuroticism may prefer more conventional popular music partly to avoid the negative affect-inducing properties that they perceive in more arousing music. The measuring instruments used in above-mentioned studies were the *Eysenck Personality Inventory, Little and Zuckerman Music Preference questionnaire* and the *NEO Personality Inventor* – all previously proven to be scientifically valid and reliable instruments.

- In a publication entitled *Pain Attenuating Effects of Preferred Versus Non-preferred Music Interventions,* Hekmat & Hertel (1993) found that music favoured by subjects increased their level of pain tolerance. Non-preferred music did not demonstrate the same effect.

- Giomo (1993) studied the perception abilities of five- and nine-year-olds in relation to affective states in music. His conclusions were that there did not exist a positive relation between musical training outside the school and children's perception abilities of mood in music, but that socialization factors positively influenced subjects' recognition ability of affective conditions in music. Furthermore, a difference in this connection was found between higher and lower socio-economic status (SES) groups. Finnas & Wapnick (in Giomo, 1993: 158) came to a similar conclusion, namely that higher SES groups generally preferred classical and light classical music more than other SES groups. Other analogous studies found significant connection between socio-economic status and aesthetic development, performance on various music perception tests, and the ability to recognize and label emotion (Housten, Standifer & Izard in Giomo, 1993).

- In *Cross-Cultural Comparison in the Affective Response to Music,* Gregory and Varney (1996) examined the hypothesis that the emotional effect of music in diverse cultural groups manifested itself through a learned association. They examined the affective response to musical fragments of individuals from respectively Western European and Indian cultural backgrounds. The results suggested that cultural tradition was a greater determining factor of individuals' affective response to music than inherent musical qualities. The study showed that there were no significant differences in the affective response to music between male and female subjects. Furthermore, the authors came to the conclusion, in agreement with the work of Konečni (in Gregory & Varney, 1996) that, in general, for all the different types of music, the most frequently used reported adjectives very often do not agree with the presumed intentions of the composer. Resultantly, the artists' message frequently does not reach the listener.

- Research conducted by Crowder, Kastner, Umemoto, Heinlein and Hevner (as cited in Hoshino, 1996:29) proved that the Western European musical modes of major and minor respectively had a positive- and negative emotional undertone for individuals from this cultural background. Consequently, these modes manifested as one of the most compelling expressive devices in the suggestion of emotion. In accordance with these studies, Hoshino (1996) examined the emotional reaction of various diverse groups to the different musical modes that at present exist in Japan, namely those based on a western tonal system and modes originating from traditional Japanese music. The results illustrated that each mode produced a different impression (according to the melodic type) on the subjects, as well as additional differences in the emotional modal characters according to age group and to whether the subjects were musicians or non-musicians.

- In a study titled *Emotional expression in performance: Between the performer's intention and the listener's experience,* Gabrielsson and Juslin (1996) examined the emotional expression in musical performances with a focus on the relationship between the performer's intention and the listener's experience. They found that listeners are generally reasonably accurate in their decoding of the performer's emotional intention, and that some basic emotional entities like *happiness, sadness* and *anger* can be communicated more easily than other emotional characters e.g. *solemnity.* In addition, it seems likely that the various instruments used in the study differ with respect to their suitability for expressing particular emotions. For instance, it is more difficult to convey anger on the flute and solemnity on the electric guitar (Gabrielsson & Juslin, 1996:87).

- Juslin (1997) conducted an experimental study where he asked professional guitar players to express four emotions in the same musical sequence. The performances were examined according to musical cues like sound level, tempo, and articulation. Juslin found that the expressive objectives of the musicians affected all of the examined constructs; that the cues only had a probabilistic association with the performers' intentions; and that the music constructs were interrelated. A validating listening experiment proved that listeners effectively perceived the aimed at emotional expression and demonstrated no differentiation between musically trained and untrained listeners.

Shortcomings of the above mentioned studies – which bear relevance to the thesis – are the non-South African contextual nature thereof and a focus outside the domain of advertisement music.

In addition to these rather general music psychological inquiries, many scholars have recently focused on the functionalities of music as a source of emotion in film. The author believes that invaluable information derived from studies on film music can be made applicable to advertisement music. Both film and advertisements aim to match appropriate music to visuals with the intention to effectively communicate a specified meaning – focusing extensively on cognitive and emotional meaning. Accordingly, both of these media profoundly rely on music to assist in achieving this goal. Furthermore, due to a noticeable lack of formally conducted, theory-based research on advertisement music, one cannot afford to disregard noteworthy contributions of related fields such as film music.

In 1999, Cohen presented a number of functions which music fulfills in film or multimedia situations.[55] She states that emotion is pertinent to six of these functions (Cohen, 2001: 263). Film music enhances the *narrative's continuity*; it adds to the *emotional meaning* of events; - *stimulates mood*; - establishes and activates *memory*; - sustains *arousal and attention* to the film as a whole; augments an associated *sense of reality*; and contributes to the *aesthetic effect* of the film. Cohen further claims that in these functions music adds authentic emotional experiences in film – it complies with the criteria for a *genuine emotion* as described by Tan (1996):-[56]

- *Control precedence* – emotion induced by background music can control the listener's emotional reactions. This can be ascribed to bottom-up processing of stimuli, or higher-order top-down stimulus processing.

- *Law of concern*: emotion entails identifiable concern – if music is paired with other media, it has the ability to direct a subject's attention towards a specified object. In this regard, Cook (1998) provided some examples made applicable to the field of advertising.

[55] For a detailed description of these eight functions, the reader is referred to the identified source.

[56] Tan's criteria are also cited in Cohen (2001: 263-264).

- *Law of situational meaning* (or stimulus specificity) – All emotions possess a collection of identifiable traits of the stimulus. Numerous scholars[57] have classified these musical stimuli with their associated characteristics. They also revealed similarities between them and emotions portrayed visually (through gait, posture and speech intonation).

- *Law of apparent reality*: the stimulus must represent some reality or other – by accentuating significant events, amongst others, music adds to the narrative's sense of reality.

- *Law of change*: emotion responds to changes in the situation – music accompanying visuals establishes a dynamic auditory environment where expectations and implications are generated.

- *Law of closure*: an emotion tends towards complete realization of its appraisal and action tendency, and is relatively immune to outside influences such as conscious control. Particularly in a dark cinema, the film music will demand attention. The emotions produced through music are directed by the tension and resolution established by the music, which the audience is oblivious to, and over which diminutive control can be executed. Jourdain (1997) found that emotional responses can be reproduced by music which is heard for a second time – regardless of earlier expectations.

Following these theoretical contributions from film studies, it is apparent that music is an important source of emotional activation. Employed astutely, background music for visuals such as film and on-screen commercials could indeed be a very powerful communicative tool.

4.1.2 Cognitive Science

Considerable contributions were made in Cognitive Science as applied to music – many of these in the field of the Neuropsychology of Music. According to Peretz (2001:127), although this field is still in the early stages of development, scholars have already made valuable contributions to the understanding of the neural underpinnings of emotion related to music. She claims that it is clear that there is no fundamental *unitary emotional system* subjacent to all emotional responses to music. Recent inferences rather demonstrate the existence of explicitly identifiable neural arrangement for specific musical emotions.

---

[57] Refer to Juslin & Madison (1999), Krumhansl (1997) & Juslin (1997).

Subsequently, a summary of a few studies chosen from the extended range available, are presented in a chronological sequence. Note that this selection serves only as a preliminary exploration of research conducted within the Cognitive Sciences – an all-inclusive account of related research studies falls outside the scope of this dissertation.

- Lerdahl and Jackendoff (1983) aimed at constructing a theory of tonal music in accordance with the principles of Cognitive Psychology.

- In an article entitled *Tonal cognition, Artificial Intelligence and neural nets,* Bharucha & Olney (1989:341) claim that cognitive structures, referred to as *perceptual schemas,* mediate cultural influences on people's perceptual interpretation of music. These representations encode the regularities of genres through prolonged passive exposure to music. Bharucha (1987) previously claimed that perceptual schemas create expectations based on musical contexts, facilitate the recognition of expected patterns, and depict anticipated notes more consonant than others. Furthermore, this knowledge is implicit and not dependent on formal musical training. In their examination, which focussed on Western and Indian harmony, Bharucha & Olney employed ANNs to explain the manifestation of perceptual schemas in musically untrained subjects. They also used the networks to generate musical expectations based on these cognitive structures. They argued that ANNs can generate explicit hypotheses concerning the process through which individuals from one culture perceive the music of another.

- Although it remains uncertain which precise structures in the brain are connected to emotional reactions, the contemporary employment of novel instruments have contributed much to the matter. Hinrichs & Machleidt (1992) proved that happy and sad music respectively demonstrated different electroencephalographic (EEG) coherence effects on the human brain. An EEG provides patterns of the electrical activities of the brain. Related to this type of inquiries, the EEG serves as a descriptor of neural activities subjacent to psychological models. In a similar study, Panksepp et al. (1993) ascertained that sad music produced more arousal (*alpha blocking*) than happy music.

- Janata & Petsche (1993) claim that musical expectancies are a dynamic process, and that the generation and revision thereof is essential to the understanding of music. They studied musical expectancies (related to resolving cadences) through the EEG parameters of amplitude and coherence. They came to the conclusion that the EEG values were significantly influenced by the completion or violation of established musical contexts (expectancies). The results not only confirmed their hypotheses that a type of expectancy does operate in musical contexts, but also revealed the activation of particular brain structures[58] subjacent to the processing of complex musical stimuli.

- Tramo (1993) studied the biological basis of musical perception and -cognition by examining musical perception of brain-damaged individuals. He examined subjects whose left and right cerebral hemispheres had been surgically separated, in order to assess the role of each half-brain in music processing. Tramo emphasized the need to use real-world musical sounds rather than laboratory-contrived acoustical stimuli when investigating brain mechanisms in music.

- In his research on the perception and cognitive imaging of Northern Indian music, Vaughn (as cited in Cross & Deliège, 1993) used experimental techniques related to the field of Psychology.

- Parncutt (in Cross & Deliège, 1993) examined the influence of psychoacoustical factors on the perception of harmonic structure by different individuals.

- Panksepp (1995:171) states that music can change people's moods and emotions by interaction with the brain in ways that are not yet fully understood. One type of emotional effect that music can produce is a *chill*, described as a *shivery, gooseflesh type of skin sensation.* He claims that these chills may be evidential of the brain's capability to obtain specific types of emotional meaning from music. His research indicated a correlation between chills and the perceived emotional content of different pieces of music, with a significantly greater relation to perceived sadness than happiness. In his study, female subjects experienced more chills than their male counterparts. Panksepp makes the assumption that, since sad emotional states are habitually caused by a loss of established social connections, there may be a fundamental neurochemical resemblance between the chilling emotions caused by music and those caused by social severance.

- In a study titled *Learning Musical Structure and Style with Neural Networks,* Hörnel & Mentzel (1998) examined the neural information structures which play a role in musical thoughts. The aim was to develop artificial neural networks that can learn the structural characteristics of a composer's personal style, resulting in the identifying and reproducing of these musical styles and structures.

- In *Brain Imaging Studies of Musical perception and Musical imagery*, Zatorre (1999) examined the brain activity of normal-functioning individuals in a laboratory. He studied the musical cognition processes of melodic perception and musical imaging and made prominent contributions towards the understanding of the neurological basis underlying musical processes. The paper also illustrated appropriate methodologies for the systematical studying of complex neural processes subjacent to musical

[58] In particular, the EEG parameters changed at recording sites above the auditory cortices and above the frontal and parietal areas.

cognition, which in turn could lead the way to more complete theoretical models concerning musical cognition.

- In *Methodologies of Brain Research in Cognitive Musicology,* Tervaniemi & van Zuilen (1999), in order to examine the operation of the human brain, looked into the most common non-invasive methods which are currently used in the field of Neuroscience. The functionality of these methods (EEG, MEG, PET, fMRI) to depict the neural functioning underlying musical perception, are discussed in a theoretical work. The authors identified an important shortcoming in research within this field: up to now, there is inadequate research on the topic of emotional changes in people when exposed to music, and the relation with subjacent neural functions.

- Schmidt & Trainor (as cited in Juslin & Slobada, 2001), measured people's brain activity on selected music from the classical repertoire by employing EEG-techniques. They found a greater left frontal activation to music that expressed joy and happiness and greater right frontal activation to music depicting fear and sadness.

4.1.3 Consumer Science

As stated in the introduction, advertising is the means by which one party tries to convince another to purchase a particular product or service. As it is aimed towards an extended and very general audience, advertising depends completely on mass media and consequently on widespread social meanings rather than personal or idiosyncratic motivations for purchasing. Huron (1989: 560-569) listed the uses of music to accomplish effective broadcast advertisements:-

- Music adds to the *entertainment* value of commercials. In this manner it makes advertisements more effective by attracting the listener's attention. Huron states that it is not explicitly required that effective music holds a special affinity towards the advertised products.

- Consumers prefer recognisable and familiar products. Music, as is demonstrated through the employment of memorable jingles in certain commercials, has the ability to affect the human consciousness to a greater extent than visual images. Accordingly, when associated with music, music adds to advertisements' *memorability* and product recall is greatly enhanced.

- Music provides *continuity* to advertisements in that it connects a series of visual images, dramatic happenings, narrative voice-overs and product appeals. It also accentuates dramatic episodes.

- *Targeting* (to concentrate on a specific audience) is a very important concept in advertising – advertisers will employ tools of which the demographic traits counterpart the desired market segment. Musical styles can be viewed as *socioeconomic identifiers*, as they have been connected to different social and demographic groups.

- Effective targeting can, to great extent, be ascribed to the creation of an advertisement's *authority*. Apart from *personal authority* establishment through *expert endorsement* and *–testimony*, music can be used efficiently to establish the credibility of commercials by *group authority*. The most significant groups are those connected with age, gender, race and social class. Differences in musical preference are closely connected to these groups; thus musical style is a valuable nonverbal *identifier*. To quote Huron in this regard:

At one time or another all of the most esteemed values of a society have been tapped by advertisers in order to assist in product sales. These values include, among others: nationalism, international brotherhood, religion, family, nostalgia, friendship, motherhood, fatherhood, health beauty, youth, adventure, elegance, mystique, humor, economy, quality, security, love, sex, and, most important, 'style'. It is arguably style which holds the greatest unconscious sway, and music is arguably the greatest tool advertisers have for portraying and distinguishing various styles (Huron, 1989:569).

- Spoken dialogue – like product appeals – appear to be less self-indulgent and naïve when set to music. In commercials this connection between *speech and song* is taken advantage of. Factual information is typically communicated through spoken language, whereas emotional, non-factual messages are reserved for *lyrical language*.

Besides this, Zager (2003) holds the opinion that although composition contains many different stages and expertise, from a listener's perspective the final product is always a type of emotional reaction. For this reason he claims that composers of music for television and radio commercials must focus on generating this emotional reaction. He argues that music has the ability to induce any possible mood through the composer's preference of instrumentation, harmonic structure, compositional style, recording technique and synthesizer effects.

Huron (1989:558) holds the view that people working in the advertising industry have an extensive body of formal and informal theories at their disposal, built up through an abundance of experimental testing. They have practical experience in the identifying of social meaning that underlies the various musical styles. To quote the author: ...*one must recognize that the field* [of advertising] *represents a large body of* *empirically tested heuristics concerning social facets of music. Despite their fallibility, advertisers have considerable practical experience in joining images and music to social and psychological motivations. Ad agencies are, in essence, research institutes for social meaning.* This view is in contrast to that of Stilwell (2001: 169), who identifies inadequacies related to music in the advertising business: *Though music is present in almost every commercial on television, advertising agencies tend to know very little about music and therefore to use it conservatively. Against that trend music has increasingly merged with sound design in the creation of evocative soundscapes.*

All the same, a number of pertinent studies had been accomplished within the field of Consumer Science, and had been published in, amongst other, the *Journal of Advertising Research, Journal of Consumer Research, Advances in Consumer Research* and the *Journal of Marketing.* Although these studies were not specifically approached from a musicological point of view, the following findings bear relevance to this research endeavour:

- Infante & Berg (1979) examined the effects of modality on people's perception of communications. They tested subjects on video sequences accompanied by a newly composed melody, successively performed in a major and minor key. The study demonstrated that a major modality had the highest positive effect on subject's perceptions when viewing an unlikeable situation and when facial expressions were sad or neutral. The choice of key did not influence the assessment of pleasant situations, or the perception of cheerful facial expressions.

- With reference to previously conducted empirical studies, along with psychological theories which state that advertisements which are liked (and consequently influences listeners' perceptions positively) are more effective, Aaker & Bruzzone (1981) examined subjects' positive and negative reaction to prime-time television advertisements. The authors came to the conclusion that viewers' perceptions affect the general effectiveness of television advertisements. They found three distinct ways to generate positive attitudes toward a commercial: to make it entertaining by increasing the amusement value; to make it warm (for example by focusing on the family or relationships between friends); and to make it personally relevant by involving useful information.

- A similar study examined the impact of *warmth* on the effectiveness of advertisements (Aaker et al., 1986:366). Warmth was defined as a positive, mild, volatile emotion involving physiological arousal and precipitated by experiencing directly or vicariously a love, family or friendship relationship. A relation was found between warmth and arousal (measured by skin response), as well as warmth and responses to ads and buying behaviour. In addition, the desensitization of the effect of warmth in a succession of warm advertisements was demonstrated.

- Sherry (1986) made an important contribution in a study titled *The Cultural Perspective in Consumer Research*. He held the opinion that a cultural perspective in the interpretation and application of consumer-studies could assist researchers in achieving a comprehensive understanding of the specific consumer behaviour which they were attempting to interpret. The interpretation will be a synthesis of the consumer's native intuition and the researcher's understanding.

- Muncy (1986) made a theoretical contribution to the debate about the relation between cognition and affect. His conclusion was that researchers in the field of Consumer Science should pay more attention to the relationship between cognition, affect and consumer preferences.

- Edell and Burke (1987) examined the impact of feelings in understanding advertising effects. They found that positive and negative feelings co-occur and that both are important predictors of the effectiveness of the ad. They concluded that feelings contribute uniquely to attitude toward the ad, beliefs about the attributes of the brand and attitude toward the brand.

- The aim of Holbrook and Batra's research (1987) was to incorporate an adequate representation of the full range of emotional reactions into an exploration of the role of emotions in mediating consumer responses to advertising. Their main finding was that three emotional dimensions, namely pleasure, arousal and domination, mediated the effect of advertising content and attitude towards the advertisement or brand.

The following research studies have specific relevance to the focus area of advertisement music.

- A study examining the influences of music on commercials, proved that background music can indeed become associated with the concerned product in the humanoid memory system (Gorn, 1982). Subsequently, product choice will be influenced by this process of classical conditioning. Gorn also found that, whenever test subjects were not in a *decision-making mood*, the employment of background music enhanced the impact of a commercial more than the provision of product information. He concluded that classical conditioning could facilitate the association of products with the positive feelings of liked music.

- Gardner's (1985) definition of mood – that it is a temporary feeling state, typically not very extreme, and not linked to a specifiable human behaviour – was employed by Alpert & Alpert (1990), who studied the relationship between music and consumers' moods, attitudes and behaviours. They stated that moods can either be positive or negative, like cheeriness, peacefulness, guilt or depression. Emotion, in contrast, is associated with specifiable behaviour and described as being more intense and apparent than moods. A number of research studies[59] cited in Alpert & Alpert proved that instrumental background music with a slow tempo could noticeably slow down the pace of supermarket shoppers and people dining in restaurants. In this regard, Smith & Curnow (1966) found that customers will spend considerably more time in a store when the music is soft compared to loud music.

- Bierley, McSweeney & Vannieuwkerk (1985) found that stimuli which preceded enjoyable music were favoured significantly more than stimuli which were followed by silence.

- Nel (1991) examined the effect of background music and involvement of ads on the viewer's demeanour towards advertisements, brand names and buying intention. The study was conducted in a South African context, and concluded that background music had a significant influence on a consumer's attitude towards an advertisement.

- In the article *Music and meaning in the commercials* (1994), Cook examined the communicational role of music in a contemporary multi-media context.

- *Die invloed van indeksikaliteit en gepastheid van advertensiemusiek en betrokkenheid van verbruikers op verbruikers se reaksie teenoor advertensies* is the title of Van den Berg's (1995) thesis. An important inference was that aptness of advertisement music has a significant influence on consumers' emotions and their attitude towards ads. A significant positive connection was found between aptness of advertisement music, emotion and involvement. A further finding was that aptness of ad music also influences listener's attention to the music, attitude towards brand name and association with previous experiences. This study is one of a few which is conducted in a South African context within the field of industrial Psychology, with fundamental resemblance to the study at hand. Relevant shortcomings, however, are the lack of an interdisciplinary approach and a multicultural focus.

- Bigand, Parncutt and Lehrdahl (1996) examined the effect of four variables (*tonal hierarchy, sensory achordal consonance, horizontal movement and musical training)* on subjects' perception of tension in music. The main outcome of the enquiry was that the experience of tension is caused by various converging cognitive and psycho-acoustical factors. The relative importance of the latter varies in relation to the level of musical training.

To conclude this review, a citation by Zager (2003: xi):-

A study by the Harvard Business Review concluded that people remembered 20 percent of what they hear, 30 percent of what they see, and an astounding 70 percent of what they hear and see.

[59] Refer to Milliman (1982, 1986).

4.2 COMMENTS ON LITERATURE REVIEW

The examples from the review, which represent only a few cases from an extended and diverse field of knowledge, provide ample evidence that one can indeed obtain successful advertising results when exploiting the human affections – amongst others – through the employment of music. As stated in the introduction, there is a noticeable void of research focusing on a better fit between commercials and music.

The few studies that were accomplished, lacked an interdisciplinary approach to their research questions and, very importantly, did not actually apply their theoretical findings in a practical manner across the boundaries of their various fields. The author is of the opinion that every one of these disciplines has an abundance of insights to offer, and by sharing results much can be achieved in the understanding and exploiting of the functionality of emotion in advertising. Thus, although most of the cases discussed in the review do not focus on a South African commercial music environment, nor were they conducted with the specific aim to enhance the suitability of advertisement music, their contribution in making inferences in this regard cannot be overlooked.

Following the literature review, it becomes apparent that the subject of the influence of advertisement music on consumer behaviour could potentially be an exceptionally broad one. In fact, to fully comprehend it, would imply a complete understanding of human cognition and the functionality of the human brain. Unfortunately, we still have but a glimpse of an understanding of both of these fields. However, by exercising a multidisciplinary approach to the issue and combining information from these various disciplines, our comprehension thereof will unquestionably increase.

Apart from musical structure – which research had been focussed so far, there are many other aspects of music that could potentially have an impact in this regard. These include lyrics, artistic interpretation, the kind and period of music, particular memories that may be connected to the music, to name but a few (Alpert & Alpert, 1990). One must also take into consideration the interaction of these factors with the advertised product and use-situation as emphasized in the commercial.

We have not yet recognized all of these role-playing factors, but a combination of these studies that had been conducted on the subject over the past few decades and coming from different paradigms, is one step in the right direction. Scherer & Zentner (2001: 365) present an interesting *multiplicative formula* in an attempt to encapsulate the multifaceted and highly intricate process of emotional generation in human subjects when listening to music. A synopsis of their theory is presented in figure 4.1.

Fig. 4.1 A scheme to describe the intricate process of emotional generation

experienced emotion = structural features × performance features × listener features × contextual features

structural features	performance features	listener features	contextual features
segmental features × suprasegmental features	performer skills × performer state	musical expertise × stable dispositions × current motivational/mood state	location × event

Directory of terminologies (based on Scherer & Zentner, 2001: 362-365)

- Structural features: attributes of a score that the performer needs to acknowledge
- Segmental features: acoustic traits of the components of musical structure (separate sounds produced by voice or instruments). These effects on emotion inference are usually manifested through iconic coding, and typically stable and universal.
- Suprasegmental features: systematic configurational changes in sound fragments over time, e.g. intonation, amplitude contour in speech, melody, tempo, rhythm etc. Emotional information is transmitted mainly by means of symbolic coding, although iconic coding also plays a role.
- Performance features: performer's rendering of the music, based on iconic and symbolic coding.
- Performer skills: the performer's identity (physical appearance, expression, reputation), as well as his/her technical and interpretative capabilities.
- Performer state: the performer's interpretation, concentration, motivation, disposition, stage presence, etc.
- Listener features: the listener's individual and socio-cultural identity, and symbolic coding convention prevalent in a certain culture or subculture. Emotion is induced through iconic- and symbolic coding, as well as through associative coding.
- Musical expertise: collective interpretation rules of a group or culture, cultural beliefs about musical meaning, inference dispositions founded on personality, previous experience, musical talent.
- Stable dispositions: personality or perceptual conventions, unconnected to music.
- Current mood state: temporary conditions e.g. concentration, motivational state, current mood.
- Contextual features: features of the performance / listening situation –include physical setting and type of event. The objective features of the situation or subjective perceptions of the audience cause emotional effects.

Alpert & Alpert (1990) argue that research may eventually reach such a level of sophistication that these overall musical effects could be divided into theoretical elements and their constituents. Such research would take into consideration the influence of intermediary variables like subjects' personalities, -demographics, their way of living, -cognitive and affective involvement in the communication setting and acquaintance with the music. The authors claim that although this is a great challenge, it is encouraging to realize that predictions from musical theory, which demonstrate a correlation to people's emotional responses, may be derived. Alpert & Alpert also argue that if future research could validate these issues, it would be feasible to more fully comprehend this source of emotional response to advertisements. This would facilitate the screening of potential commercials for predicted influences.

As illustrated throughout the review and again emphasised in Scherer & Zentner's equation, the challenge to fully understand the extent of the power of music in commercials, is considerable. An understanding means better spot-on commercials that demonstrate the desired effect on potential customers and consequently, put blatantly, more money for businesses; therefore it is also a well-founded goal to pursue. Equally great is the challenge to intelligently and purposefully map, incorporate and apply this knowledge in the field of advertising – preferably as much data that can be derived from as many fields as possible. Thus, a methodology which w to provide the option to be expanded as new research becomes accessible, is needed. In this regard the author believes an ANN methodology is the paramount choice to accomplish such a goal.

4.3 METHODOLOGICAL CONSIDERATIONS

It was previously established that ANNs can learn intricate relationships between variables and are therefore most applicable to problems involving pattern recognition, classification, prediction, and forecasting. According to Smith (1999), successful network performance depends on the accuracy and generalizability of the learning process. It is the researcher's responsibility to use certain methodological procedures which will guarantee that the network has learnt the underlying patterns of the data, and not merely memorizes the training sample. Thus, in planning the simulated musical network, a few methodological issues should be taken into consideration. The methodological process in constructing an ANN is in many ways similar to the process of conventional statistical procedures employed by the Social Sciences, therefore standard terminologies familiar to statistics are typically employed in discussions of this sort. For any uncertainty regarding any of the terms used, the reader can consult Babbie (2004), Howell (2004) and Mouton (2001).

4.3.1 Deciding on an appropriate model and selecting the software

As stated before, ANNs are usually a good choice when the research problem is ambiguous, unstructured and engage extended collections of competing inputs and constraints; also whenever the data at hand is vague, noisy, overlapping, non-linear and non-continuous. Adding to this, in the words of Dolson (1991), neural networks are an appropriate preference whenever one wants to synthesize a behaviour for which examples are more easily attained than algorithms. Smith (1999) and Betratti et al. (1996) argue for the employment of ANNs to study economics and business-related problems, and Mouthino et al. (1994) explicitly state that it is suitable to employ neural network techniques to study the impact of advertising on consumers. From the preceding chapters, enough evidence is presented to authenticate the author's choice for this specific tool in examining South African advertisement music.

Nowadays, the prevalent quantity of applications for neural modelling is by means of computer software, although there are many efforts to design *neurocomputers – hardware that emulate neural networks through parallel processors in the computer* (Garson, 1998: 111). Today scholars can choose from a vast collection[60] of available neural network software packages, most of them running on a PC under Microsoft Windows®™. Additionally, the option is available to program your own ANN software (Dewdney, 1992). There are also numerous packages available for downloading on the World Wide Web, many of them available as shareware and freeware. In this regard, an extended list of commercial neural networking packages, freeware and shareware can be found at the following URLs:

ftp://ftp.sas.com/pub/neural/FAQ6.html

http://dmoz.org/Computers/Artificial_Intelligence/Neural_Networks/Software

Two examples of software applications typically employed in social scientific research are *Neural Connection* and *NeuroShell.* Additionally, a list of software used in a broad spectrum of applications include *NeuralWorks, Neural Net Oracle, Annie, Cotrex, Neurak, Stuttgart Neural Network simulator, Tiberius, EasyNN, Simbrain,* and the *Neural Network toolbox for MATLAB.*

4.3.2 Constructing and training the network

As previously stated, rationalizations fundamental to the humanities relate to neural modelling as well. Smith (1999) and Garson (1998) stipulated a few issues on dealing with the independent variables (input variables), training sample, and output variables (dependent variable).

[60] Reid & Zeichick (1992) present a review of 50 commercial ANN packages.

- It is advantageous to equal the number of input neurons and the amount of potential values for each independent variable (output units). In this way one is not compelled to handle ordinal data as interval, and the managing of nominal data is possible. The network will also yield better results by normalizing input data through statistical procedures, or simply by avoiding the employment of raw data by using ratios, percentage change, indexing, or other types of relative measures.

- Input variables that lack explanatory potential due to their invariance over the range of the dependent variables, should be eliminated from the network.

- Extreme cases can interfere with the computation of weights used in prediction, therefore outlier data should be removed or set to a limit.

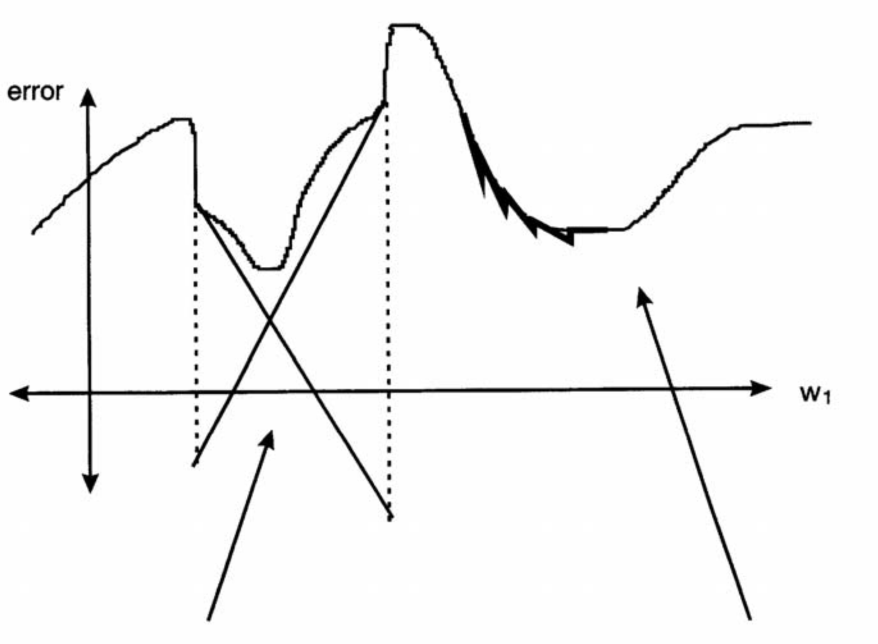
- Generalization will be negatively affected if the training sample is mined form a different environment (e.g. time dimension) than those used for testing and generalization.

- Garson (1998) states that similar to all types of data analysis, the significance of ANN's output is a direct function of the extent to which the inputs contain the causal variables for the dependent variable. Although it is desirable to employ a great amount of inputs, it is crucial to filter out insignificant and irrelevant variables. ANNs learn to disregard excessive input variables, but generalization will be negatively influenced if essential inputs are absent.

- Concerning the training data set, the selection, amount, and order of training samples are very important issues. The optimal training samples are not randomly selected, but rather carefully chosen by the researcher on the basis of the conceptual attribution of each example to the network. Regarding ANNs, randomized samples hold the potential to overstate some underlying relationships while disregarding others. When deciding on the quantity of training patterns to be used, one should keep in mind that increasing the number of examples will increase the training error and decrease generalization error. Generally, using less than 50 will not yield adequate results. Garson (1998: 88) claims that the amount of training examples should at least equal 10 times the number of input and middle layer neurons. Lastly, the order of presenting the training data to the network can potentially affect its functionality. If the training examples are assembled in a certain significant order, the network will learn successively starting by the first group, and will be biased towards the last data-input.

- Another important issue is the choice of training rate, which will determine the quantity of each weight's adjustment during every pass through the algorithm. Smith (1999) claims that, similar to finding the right number of hidden units, the optimal training rate is determined by a balance between values that are too high or too low. She states that the learning rate should be in the range between 0.0001 to 10. Figure 4.2[61] demonstrates the effects of inappropriate learning rates.

Fig. 4.2 Choice of learning rate



Large learning rate:
weight modification is too much – the local minimum could be continuously overstepped, causing oscillation from side to side, and never reaching convergence to the lower error state

Small learning rate:
too little weight modification – the number of iterations will be needlessly large, producing a slow performance

- Concerning the output layer, a network will compress inputs into outputs when the number of output units is less than the inputs. This type of model can extract the most important components from noisy data, which is an attractive application for the Social Sciences in general and the study at hand.

---

61 Cited from Smith (1999: 53).

4.3.3 Interpreting the results

Since ANN models do not compel scholars to presume a model explicitly connecting inputs to outputs as statistical methodologies do, the understanding of results are not so clear-cut, and could be challenging to interpret.

Garson (1998) provides two types of post-analyses strategies that could assist the researcher in this endeavour. The training sample can be grouped according to estimated values of the output variables. High and low categories can accordingly be separated in order to analyse their input traits. Secondly, the variation between the neural model's calculated approximation and actual values can be *residually* examined in order to identify variables that are omitted from the model. High residuals can also advocate the necessity for multiple models associated with particular categories of the population of examined cases.

In closing, Garson claims that due to its distribution of computation through the entire network, causal analysis could be problematical when employing ANNs. When examining results from a neural model, one needs to focus on the output rather than the input layers' connection weights, because the weights connecting the input- and output units reveal the relative predictive significance of the independents. In closing, he argues that the interpretation of neural models is frequently restricted to the evaluation of their classificatory or predictive efficiency.

4.4 IMPEDIMENTS TO THE USE OF ANNS IN THE SOCIAL SCIENCES

Despite the strong case which is argued for the employment of ANNs in Social Scientific research, this field still prefers to use more traditional research methodologies, like statistics. There a few reasons explaining why the application of ANNs are very exclusive in the Social Sciences:

Firstly, the ANN-approach is still very young and adequate software was only developed in the 1990s. Secondly, because ANN-models demonstrate limitations regarding causal analysis, it can be problematical to comprehend how results are concluded in such a system. The third reason for the limited use of ANNs in the Humanities is that – in the past – their inclusion in standard statistical packages has progressed very slowly. However, this has been changing gradually over the last few years, and there might be a growth in the employment of ANNs in the near future. Another reason is that

ANNs, which originated from paradigms very different to that of the Social Sciences, use another 'language' and a different set of terminologies, which could be confusing to scholars in this field. Garson (1998:17) provides a few examples, the first of each case being representative of Social Scientific jargon:-

- *Cases / observations are called* patterns*; variables are called* features
- *Independents are called* features*; dependents are* targets *or* outputs*; residuals are identified as* errors*;*
- *Estimation is called* training, learning *or* self-organization*; validation is* generalization.

Finally, ascribed to the huge quantity of different neural network architectures that is currently available, researchers in the Social Sciences sometimes become resistant to take the time and effort to explore the best option for every specific application.

References

Aaker, D.A. & Bruzzone, D.E. (1981). Viewer perceptions of prime-time television advertising***. Journal of Advertising Research,*** (21/5), 115- 23.

Aaker, D.A., Stayman, D.M. & Hagerty, M.R. (1986). Warmth in Advertising: Measurement, Impact, and Sequence Effects. ***Journal of Consumer Research,*** (12), 365-380.

Alpert, J. I. & Alpert, M. I. (1990). Music Influences on Mood and Purchase Intentions. ***Psychology and Marketing,*** (7/2), 109-133.

Babbie, E. (2004). ***The Practice of Social Research – Tenth Edition.*** Belmont, CA: Wadsworth Publishing Company.

Beltratti, A, Margarita, S. & Terna, P. (1996). ***Neural Networks for Economic and Financial Modelling.*** London: International Thompson Computer Press.

Bharucha, J. J. (1987). MUSACT: A connectionist model of musical harmony. ***Proceedings of the Cognitive Science Society.*** Hillsdale, NJ: Erlbaum.

Bharucha, J. J. & Olney, K. L. (1989). Tonal cognition, Artificial Intelligence and neural nets. ***Contemporary Music Review,*** (4), 341-356.

Bierley, C., McSweeney, F. K., & Vannieuwkerk, R. (1985). Classical Conditioning of Preferences for Stimuli. ***Journal of Consumer Research,*** (12), 316-323.

Bigand, E. Parncutt, R. & Lehrdahl, F. (1996). Perception of musical tension in short chord sequences: The influence of harmonic function, sensory dissonance, horizontal motion, and musical training. ***Perception & Psychophysics***, (58/1), 125-141.

Cohen, A. J. (1999). The functions of music in multimedia : A cognitive approach. In Yi, S. W. (ED.). ***Music, mind, and science,*** (53-69). Seoel, Korea : Seoel National University Press.

Cohen, A. J. (2001). Music as a source of emotion in film. In Juslin, P. N. & Slobada, J. A. (Eds.). ***Music and Emotion,*** (249-272). Oxford: University Press.

Cooke, D. (1990). ***The Language of Music.*** New York, USA: Oxford.

Cook, N. (1994). Music and meaning in the commercials. ***Popular Music***, (13/1), 27-40.

Cook, N. (1998). ***Analising musical multimedia.*** Oxford, UK: Clarendon Press.

Cross, I. & Deliège, I. (1993). Introduction: Cognitive science and music – an overview. ***Contemporary Music Review***, (9), 1-6.

Dewdney, A. K. (1992). Computer recreations: programming a neural net. ***Algorithm: Recreational Computing,*** (3/4), 11-15.

Dollinger, S.J (1993). Research note: Personality and music preference. ***Psychology of Music,*** 21 (1), 73-79.

Dolson, M. (1991). Machine Tongues XII: Neural Networks. In Todd, P. M. & Loy, D. G. (Eds.). ***Music and Connectionism*** (3-15)**.** Cambridge, Massachusetts: MIT Press.

Edell, J.A. & Burke, M.C. (1987). The Power of Feelings in Understanding Advertising Effects. ***Journal of Consumer research,*** (14), 421-433.

Farnsworth, P.R. (1954). A study of the Hevner adjective list. ***Journal of Aesthetics and Art Criticism***, 13(1), 97-102.

Gabrielsson, A. & Juslin, N. (1996). Emotional expression in performance: Between the performer's intention and the listener's experience. ***Psychology of Music,*** 24 (1), 68-67.

Gabrielsson, A. & Lindström, E. (2001). The influence of musical structures on emotional expression. In Juslin, P. N. & Slobada, J. A. (Eds.). ***Music and Emotion,*** (223-248). Oxford: University Press.

Gardner, M. P. (1985). Mood states and consumer behavior: A critical teview. ***Journal of Consumer Research,*** 13, 281-300.

Garson, G. D. (1998). ***Neural Networks – An Introductory Guide for Social Scientists.*** London: SAGE Publications.

Giomo,C. (1993). An Experimental Study of Children's Sensitivity to Mood in music. ***Psychology of Music,*** 21 (2), 141-162.

Gorn, G.J. (1982). The effects of music in advertising on choice behavior: A classical conditioning approach. ***Journal of Marketing,*** (46), 94-101.

Gregory, A. H. & Varney, N. (1996). Cross-cultural Comparison in the Affective Response to music. ***Psychology of Music,*** (24/1), 47-52.

Gundlach, R, H. (1935). Factors determining the characterization of musical phrases. ***American Journal of Psychology,*** **(47),** 624-644.

Hekmat, H. M. & Hertel, J. B. (1993). Pain Attenuating Effects of Preferred Versus Non-preferred Music Interventions. ***Psychology of Music,*** (21), 163-173.

Hevner, K. (1936). Experimental studies of the elements of expression in music. ***American Journal of Psychology***, 48, 246-268.

Hinrichs, H. & Machleidt, W. (1992). Basic emotions reflected in EEG-coherences. ***International Journal of Psychophysiology,*** (13), 225-232.

Holbrook, M. B. & Batra, R. (1987). Assessing the role of Emotions as mediators of Consumer Responses to Advertising. ***Journal of Consumer Research,*** (14), 404-420.

Hörnel, D. & Menzel, W. (1998). Learning Musical Structure and Style with Neural Networks. ***Computer Music Journal,*** (22/4), 44-62.

Hoshino, E. (1996). The feeling of musical mode and its emotional character in a melody. ***Psychology of Music,*** 24 (1), 29-46.

Howell, D. C. (2004). ***Fundamental Statistics for the Behavioral Sciences -5th edition.*** Belmont, CA: Thomson-Brooks/Cole.

Huron, D. (1989). Music in advertising: An analytic paradigm. ***The Musical Quarterly***, (73/1), 557-574.

Infante, D. A. & Berg, C. M. (1979). The impact of music modality on the perception of communication situations in video sequences. ***Communication Monographs,*** (46), 135-148.

Janata, P. & Petsche, H. (1993). Spectral Analysis of the EEG as a Tool for Evaluating Expectancy Violations of Musical Contexts. ***Music Perception,*** (10/3), 281-304.

Jourdain, R. (1997). ***Music, the brain and ecstasy: How music captures our imagination.*** New York: Morrow.

Juslin, P. N. (1997). Emotional Communication in Music Performance: A Functionalist Perspective and Some Data. ***Music Perception,*** (14/4), 383-418.

Juslin, P. N. & Madison, G. (1999). The role of timing patterns in recognition of emotional expression form musical performance. ***Music Perception,*** (17), 197-221.

Juslin, P. N. & Slobada, J. A. (Eds.).(2001). ***Music and Emotion.*** Oxford: University Press.

Krumhansl, C. J. (1997). An exploratory study of musical emotions and psychophysiology. ***Canadian Journal of Psychology,*** (51), 336-352.

Lerdahl, F. & Jackendoff, R. A. (1983). ***A Generative Theory of Tonal music.*** Cambridge: M.I.T. Press.

Milliman, R. E. (1982). Using background music to affect the behavior of supermarket shoppers. ***Journal of Marketing,*** (46), 86-91.

Milliman, R. E. (1986). The influence of background music on the behavior of restaurant patrons. ***Journal of consumer Research,*** (13), 286-289.

Moutinho, L., Curry, B., Davies, F. & Rita, P. (1994). ***Computer Modelling and Expert Systems in Marketing.*** London: Routledge.

Mouton, J. (2001). How to succeed in your Master's & Doctoral Studies – A South African Guide and Resource Book. Pretoria: Van Schaik Publishers.

Muncy, J.A. (1986). Affect and Cognition: a Closer look at two Competing Theories. ***Advances in Consumer Research,*** (xiii), 226-230.

Nel, E. (1991). ***Die invloed wat agtergrondmusiek in advertensies en tipe en vlak van betrokkenheid uitoefen op verbruikers se houding teenoor advertensies, houding teenoor handelsmerk en koopintensie.*** (Masters thesis). Stellenbosch: US Printers.

Panksepp, J. (1995). The Emotional Sources of 'Chills' Induced by Music. ***Music Perception,*** (13/2), 171-207.

Panksepp, J., Lensing, P., Klimesch, W., Schlimke, H. Vanigan, M. (1993). Event related desynchronization (ERD) analysis of rhythmic brain functions in normal and autistic people. ***Neuroscience Abstracts,*** 19, 1885.

Peretz, I. (2001). Listen to the brain: biological perspective on musical emotions. In Juslin, P. N. & Slobada, J. A. (Eds.). ***Music and Emotion,*** (105-134). Oxford: University Press.

Reid, K.& Zeichick, A. (1992). Neural network products resource guide. ***AI Expert,*** (7/6), 50-56.

Scherer, K. R. & Zentner, M. R. (2001). Emotional effects of music: Production rules. In Juslin, P. N. & Slobada, J. A. (Eds.). ***Music and Emotion,*** (361-392). Oxford: University Press.

Sherry, J. F. (1986). The Cultural Perspective in Consumer Research. ***Advances in Consumer Research,*** (xiii), 573-575.

Smith, K.A. (1999). ***Introduction to Neural Networks and Data mining for Business applications.*** South Melbourne, Australia: Corporate Printers.

Smith, P. C. & Curnow, R. (1966). Arousal hypotheses and the effects of music on purchasing behavior. ***Journal of Applied Psychology,*** (50/3), 255-256.

Stilwell, R. J. (2001). Music in Advertising. In Sadie, S. & Tyrrell, J. (Eds.).***The New Grove Dictionary of Music and Musicians*** (2nd ed.), (1), 169 –171.

Tan, W. (Ed.). (1996). ***Emotion and the structure of narrative film: Film as an emotion machine.*** Mahwah, NJ: Erlbaum.

Tervaniemi, M. & van Zuilen, T. L. (1999). Methodologies of Brain Research in Cognitive Musicology. ***Journal of New Music Research***, (28/3), 200-208.

Thompson, W. F. & Robitaille, B. (1992). Can composers express emotions through music? ***Empirical Studies of the Arts,*** (10), 79-89.

Tramo, M. J. (1993). Split-brain studies of music perception and cognition. ***Contemporary Music review,*** (9), 113-121.

Van den Berg, K. (1995). ***Die invloed van indeksikaliteit en gepastheid van advertensiemusiek en betrokkenheid van verbruikers op verbruikers se reaksie teenoor advertensies***. (Masters thesis). Stellenbosch: US Printers.

Wedin, L. (1972). A Multidimentional Study of Perceptual-Emotional Qualities in Music. ***Scandinavian Journal of Psychology,*** (xiii), 241 – 257.

Zager, M. (2003). ***Writing Music for Television and Radio Commercials.*** USA: Scarecrow Press.

Zatorre, J. R. (1999). Brain Imaging Studies of Musical perception and Musical imagery. ***Journal of New Music Research,*** (28/3), 229-236.

CHAPTER 5: A MUSICAL NETWORK MODEL FOR USAGE IN THE FIELD OF ADVERTISING

The preceding chapters provided sufficient evidence to support a methodology which employs an artificial neural network to assist with decision-making processes related to the choice of advertisement music. In conclusion, this chapter presents the accumulation of the theoretical findings and assumptions of all of the former, in presenting a musical network model that incorporates all of this knowledge in a single tool. As mentioned previously, the main objective of this endeavour is to establish the feasibility of combining data from many diverse fields, in the creation of an ANN that can be helpful in research regarding South African advertisement music. The ultimate anticipated goal of the network will be its ability to assist in the prediction of an optimal association between advertisement music and consumer target groups.[62]

Chapter 5 will commence with a discussion of two examples of the successful employment of ANN models in the business world. As these cases demonstrate notable similarities to the objectives, methodology, and aimed at results of the musical network presented in section 5.2, they will be taken as point of departure. Following this, the proposed model will be presented and its methodology will be discussed comprehensively. The chapter will conclude with the author's suggested method of attaining a sample to train the network on in a future study.

5.1 ANN MODELS FOR BUSINESS APPLICATIONS

It has been established throughout this thesis that ANNs have been effectively employed in the field of music as well as the business world in the solving of numerous problems.[63] In regard to business applications, the reader is additionally referred to Smith (1999), Zirilli (1997), Beltratti, Margaritha, & Terna (1996), Gately (1996), Wong et al. (1995), Kong & Martin (1995), Mouthino et al. (1994), Barr & Mani (1994), Kennedy (1991), Margarita (1991), Harston (1990), and Baum (1988).

---

[62] The neural model's real functionality can only be assessed in a future study, following its performance whilst using authentic data.

[63] Refer to section 2.5, 3.4.1, and chapter 4.

Beltratti, Margaritha, & Terna (1996:65) claim that the perception of the economy as an …*ever-changing flow of relations and pieces of information* was long in the coming. They argue that this way of depicting the economy as an *evolving complex system* is significant to the way *economic agents*[64] are represented:

In a complex system agents have to continuously learn and adapt in order to respond to the external impulses. Their learning more complicated dynamics in some cases may increase the level of complexity of the system, in a sort of never-ending loop between internal models and actual models.

These authors provide motivation supporting their perception of ANNs as a methodology that can be effectively applied to problems in the complex system of Economics. They argue that ANNs can sufficiently model the learning behaviour of economic agents, and can to a certain extent reveal the way these agents learn in real situations. In this manner, an impartial basis can be established that could provide a common theme for future research. They claim that these objective foundations could possibly prefer ANNs as a paradigm and basis to compare their various models and theories. Additionally, ANNs have already been established in financial markets as imperative trading instruments.

Harston (1990: 391) argues that nearly any ANN application could be feasibly employed in one of the many themes related to business such *as marketing, financial analysis, auditing, resource allocation, scheduling, planning, personnel management, security and quality control.* He also states that neural networks demonstrate much potential in *database mining* – to find patterns embedded within explicitly stored information in databases.

In addition to this, Mouthino et al. (1994) is of opinion that the demonstration of the profitable employment of ANNs in various pattern recognition-related tasks in fields such as Engineering, provides an adequate rationality for their adaptation in a marketing milieu. Therefore, it is also undoubtedly feasible to employ ANN techniques to observe the impact that advertising has on consumers. In the following section, two authentic examples are presented that demonstrate the successful utilization of ANNs to enhance profitability in business-related situations. The first case describes the implementation of a neural network to evaluate the financial credibility of loan candidates. The second case presents a neural model which assesses the attitudes, preferences, satisfaction, and decision-making processes of users of automated teller machines (ATMs).

---

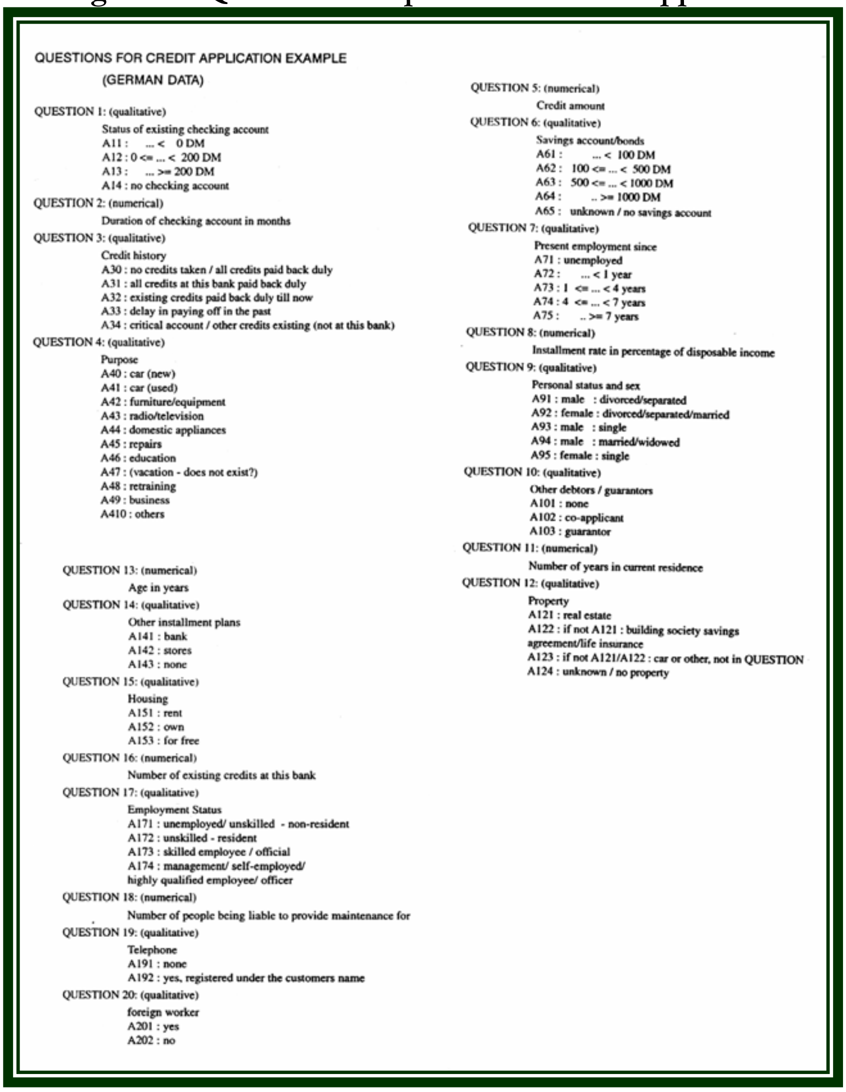
[64] According to Beltratti et al. (1996) *economic agents* are constructs that exist in complex economies. Their main task is to learn about other agents and the environment.

5.1.1 Using an ANN to assess loan applicants[65]

5.1.1.1 Research problem and data accumulation

In this example, the ANN is taught to classify bank loan applicants as good or bad credit risks – that is, to learn to distinguish between candidates who will probably repay their debt and those who will not. The classification process is based solely on information provided by candidates on their application forms. Initially, 1000 former claims – previously categorized as being good or bad applicants – were available to train the model on. These were divided into 700 examples of good applicants and 300 cases of bad applicants. The training data was acquired from a German bank and presented to the claimants as 20 personal- and financially related questions asked on the application form. A translation of the original German document is presented in figure 5.1.[66]

Figure 5.1 Questionnaire presented to loan applicants



QUESTIONS FOR CREDIT APPLICATION EXAMPLE
(GERMAN DATA)

QUESTION 1: (qualitative)
Status of existing checking account
A11 : ... < 0 DM
A12 : 0 <= ... < 200 DM
A13 : ... >= 200 DM
A14 : no checking account

QUESTION 2: (numerical)
Duration of checking account in months

QUESTION 3: (qualitative)
Credit history
A30 : no credits taken / all credits paid back duly
A31 : all credits at this bank paid back duly
A32 : existing credits paid back duly till now
A33 : delay in paying off in the past
A34 : critical account / other credits existing (not at this bank)

QUESTION 4: (qualitative)
Purpose
A40 : car (new)
A41 : car (used)
A42 : furniture/equipment
A43 : radio/television
A44 : domestic appliances
A45 : repairs
A46 : education
A47 : (vacation - does not exist?)
A48 : retraining
A49 : business
A410 : others

QUESTION 5: (numerical)
Credit amount

QUESTION 6: (qualitative)
Savings account/bonds
A61 : ... < 100 DM
A62 : 100 <= ... < 500 DM
A63 : 500 <= ... < 1000 DM
A64 : .. >= 1000 DM
A65 : unknown / no savings account

QUESTION 7: (qualitative)
Present employment since
A71 : unemployed
A72 : ... < 1 year
A73 : 1 <= ... < 4 years
A74 : 4 <= ... < 7 years
A75 : .. >= 7 years

QUESTION 8: (numerical)
Installment rate in percentage of disposable income

QUESTION 9: (qualitative)
Personal status and sex
A91 : male : divorced/separated
A92 : female : divorced/separated/married
A93 : male : single
A94 : male : married/widowed
A95 : female : single

QUESTION 10: (qualitative)
Other debtors / guarantors
A101 : none
A102 : co-applicant
A103 : guarantor

QUESTION 11: (numerical)
Number of years in current residence

QUESTION 12: (qualitative)
Property
A121 : real estate
A122 : if not A121 : building society savings agreement/life insurance
A123 : if not A121/A122 : car or other, not in QUESTION
A124 : unknown / no property

QUESTION 13: (numerical)
Age in years

QUESTION 14: (qualitative)
Other installment plans
A141 : bank
A142 : stores
A143 : none

QUESTION 15: (qualitative)
Housing
A151 : rent
A152 : own
A153 : for free

QUESTION 16: (numerical)
Number of existing credits at this bank

QUESTION 17: (qualitative)
Employment Status
A171 : unemployed/ unskilled - non-resident
A172 : unskilled - resident
A173 : skilled employee / official
A174 : management/ self-employed/ highly qualified employee/ officer

QUESTION 18: (numerical)
Number of people being liable to provide maintenance for

QUESTION 19: (qualitative)
Telephone
A191 : none
A192 : yes, registered under the customers name

QUESTION 20: (qualitative)
foreign worker
A201 : yes
A202 : no

---

65 The example is based on Smith (1999). Numerous scholars have successfully employed ANNs in similar examples within the credit industry, including Carter & Catlett (1987), Altman et al. (1994), El-Temtamy (1995), and Boritz & Kennedy (1996).

66 Cited from Smith (1999: 150-152).

Seeing that an ANN's input data must be numerical and contain meaningful *scale* and *order*[67], the original (categorical) answers to the questionnaire must be pre-processed. This is commonly attained by a technique called *1-out-of-N encoding*[68]*,* which converts a single column categorical data to several columns with binary variables. In regard to the questionnaire at hand, the necessary succession will mostly materialize spontaneously as a result of the characteristics of the questions or due to the multiple choice options; in a few cases the information has to be manipulated to fit the network. For example, question 15 describing applicants' type of housing, will be translated as –1 0 for renting; 0 1 for the candidate being an owner; and 0 0 for housing free of charge. Thus, the initial data contained 7 columns of numerical data and 13 columns of categorical data, – 20 columns (variables) in total, which will now be replaced with 24 variables by applying the 1-out-of-N encoding- technique.

The established classifier of applicants as good or bad (the output of the network) can be resembled in two ways: by using a single column of a credit category of 1 (good) or 2 (bad), or by using two columns to encode good (1 0) and bad (0 1) respectively. In this way, the researcher has the option to use a single output neuron to classify candidates according to their class number, or to train the network to categorize good applicants as 1 0 and bad ones as 0 1 by using two output nodes. According to Smith (1999), it is generally better in classification problems similar to this example, to use the same amount of outputs as there are classes.

5.1.1.2 Methodology, network architecture, and results

A multilayered, feedforward network was constructed using NeuroShell2® software from Ward Systems Inc. The network contained 24 input units, 30 hidden neurons and 2 output units. An additional 2 threshold- inputs were included in the model. The training sample was composed of a 20% randomly selected section of the data. The learning rate was selected as c = 0.1 and the momentum rate as α = 0.1. The preliminary weights were small random values in the proximity of 0.3. The input patterns were presented at random to the network. The ANN's performance was assessed on the test set every 200 epochs – training was discontinued whenever the test set error had not improved within 20 000 epochs to avert the network of memorizing the training sample.

The results indicated that the network could correctly classify applicants as being good at a rate of 90.9%, and bad ones only 46.7% of the time. The latter is explainable by the fact that the network was

---

[67] This imply that ANNs will consider inputs of 1and 2 as alike but dissimilar to, for example, 9 or 10. In addition, they will interpret an input of 2 as being closer to an input of 3 than an input of 1 is.

[68] Suppose there are *N* potential values for a given variable - which do not demonstrate an innate order - the variable is to be substituted with *N* variables, which contain either a 0 or a 1.

exposed to more examples of good applications than bad ones – it also tends to classify a candidate as bad only when it is especially certain of the case. In this example, it is more significant for the bank to accurately identify bad risks than good ones, in order to curtail its exposure to risk. Consequently, the network needs to be altered so that it can identify bad applicants more accurately (in other words, to make the amount of bad applicants as good, very little). This, in turn, will imply a smaller accurateness of good applicants – which, in this case, is in accordance with the goal of the experiment. As stated before, to obtain the most suitable neural model for the specific application, a tedious process of trial-and-error is often unavoidable, but will guarantee the best results in the end.

5.1.2 An ANN for the assessment of banking clients' perceptions of ATMs[69]

5.1.2.1 Research problem and data collection

Bank services automation is becoming a critical factor in the process of trying to attain cost effectiveness, which can then be used as a strategic competitive weapon in the financial services market. Many financial institutions have clearly embarked on the development of technology-driven strategies, which they hope will be translated in terms of customer preference and consequently, higher returns and higher market penetration (Mouthino et al., 1994:197).

The process of technologically transforming banking relies to a great extend on the imperative task that ATMs perform. In this regard, employees concerned with the bank's marketing are continuously trying to determine clients' decision-making practices and the establishment of attitudes, preferences and level of contentment with innovative computerized services. The foundations of this model of clients' behaviour are based on *service expectations, perceived risk, consumer confidence, usage rate* and *long-term satisfaction*.

In the following example, 200 subjects were selected by means of a non-probable quota sample.[70] The respondents of both sexes, aged 18 or older, were personally interviewed by trained project personnel. Interval-scaled replies were accumulated, and variables were measured by using itemized five-point rating scales.

5.1.2.2 Methodology, network architecture, and results

The multilayered network was also generated in NeuroShell, and ran on a standard 33 megahertz 486 DX PC (8 megabytes of RAM), with a maths co-processor. The model consisted of respectively 4 input- and -output neurons, as well as 4 units in the hidden layer. The input- and output- neurons were classified in the following way:

[69] Based on Mouthino et al. (1994).

[70] The questionnaire was presented to a sample of bank clients at three central localities in Cardiff, Wales.

Input nodes:

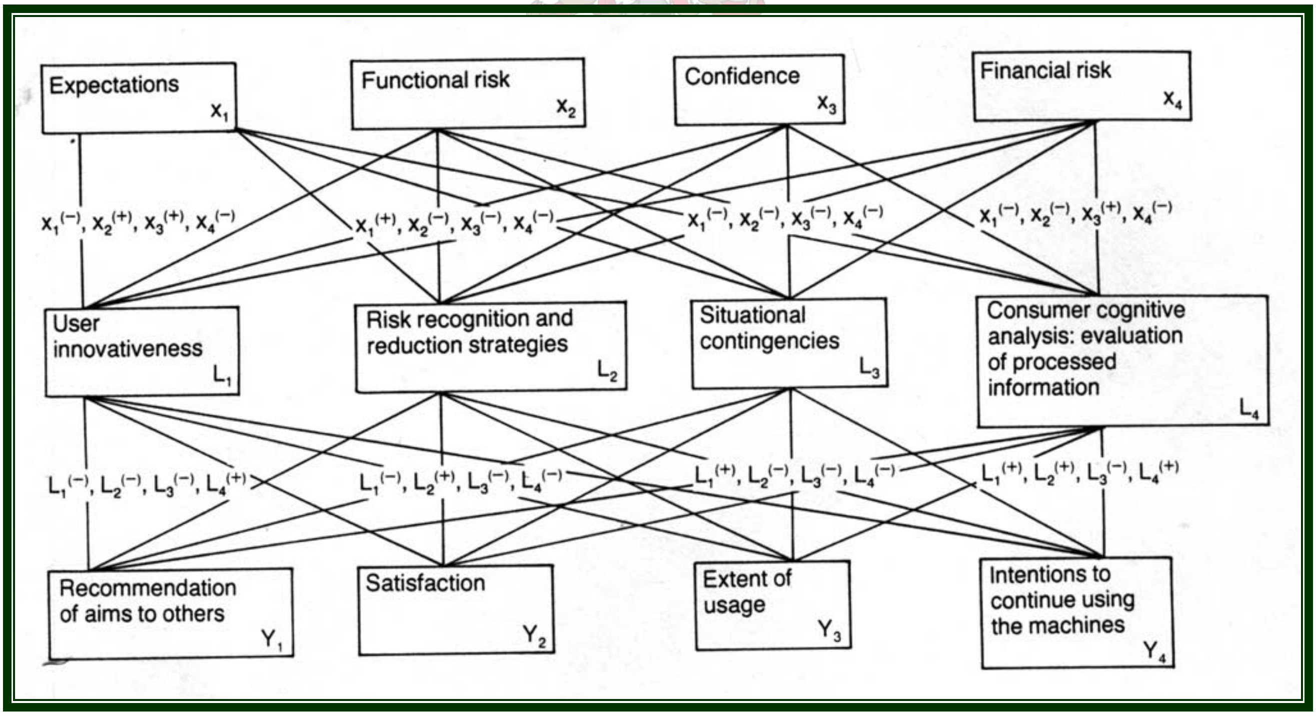
EXPECT: client expectations of ATMs; **RISKFUNC:** extent of functional risk included;
CONFID: degree of customer confidence; **RISKFIN:** degree of financial risk.

Output nodes:

RECOMM: recommendation of ATMs to others; **SATIS:** level of satisfaction;
USAGE: scale of ATM usage; **CONTINUE:** intentions to maintain ATM usage.

As hidden neurons can act as intermediate variables whose calculations are typically problematical to measure, the ANN could also measure more profound cognitive models. In this instance, the authors proposed that the hidden units represented the self-image of the client as well as aspects of service involvement. They analysed the networks connection weights according to their inhibitory and excitatory behaviour and consequently classified the hidden units, as illustrated in figure 5.2.[71] Figure 5.3 represents a summary of the learning of the model, as well as the final connection weights, displayed in NeuroShell.[72]

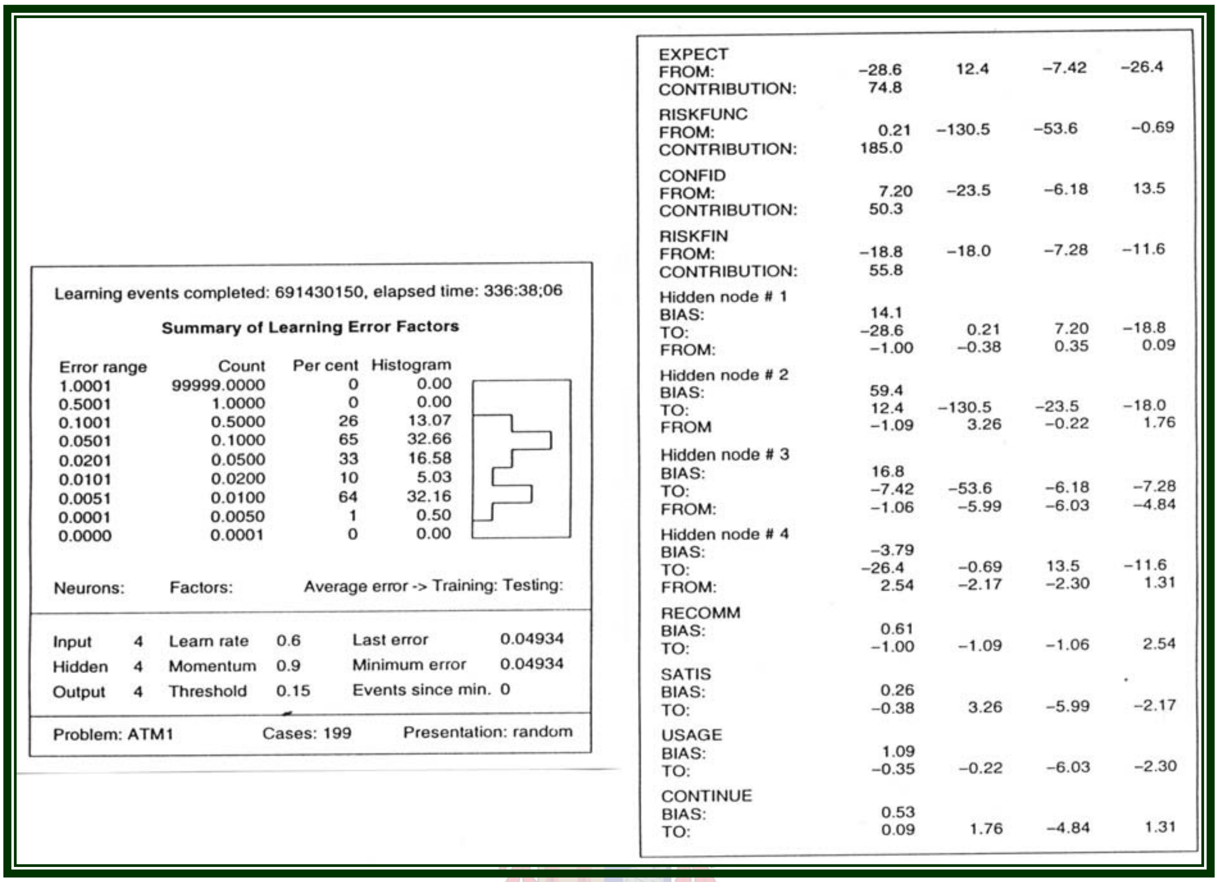
Figure 5.2 Labelling the hidden units



[71] Based on Mouthino et al. (1994: 202).

[72] Mouthino et al. (1994: 199, 201).

Figure 5.3 Learning- and connection weights of the ANN



Learning events completed: 691430150, elapsed time: 336:38;06

Summary of Learning Error Factors

Error range	Count	Per cent	Histogram
1.0001	99999.0000	0	0.00
0.5001	1.0000	0	0.00
0.1001	0.5000	26	13.07
0.0501	0.1000	65	32.66
0.0201	0.0500	33	16.58
0.0101	0.0200	10	5.03
0.0051	0.0100	64	32.16
0.0001	0.0050	1	0.50
0.0000	0.0001	0	0.00

Neurons:		Factors:		Average error -> Training: Testing:	
Input	4	Learn rate	0.6	Last error	0.04934
Hidden	4	Momentum	0.9	Minimum error	0.04934
Output	4	Threshold	0.15	Events since min.	0

Problem: ATM1 Cases: 199 Presentation: random

EXPECT				
FROM:	−28.6	12.4	−7.42	−26.4
CONTRIBUTION:	74.8			
RISKFUNC				
FROM:	0.21	−130.5	−53.6	−0.69
CONTRIBUTION:	185.0			
CONFID				
FROM:	7.20	−23.5	−6.18	13.5
CONTRIBUTION:	50.3			
RISKFIN				
FROM:	−18.8	−18.0	−7.28	−11.6
CONTRIBUTION:	55.8			
Hidden node # 1				
BIAS:	14.1			
TO:	−28.6	0.21	7.20	−18.8
FROM:	−1.00	−0.38	0.35	0.09
Hidden node # 2				
BIAS:	59.4			
TO:	12.4	−130.5	−23.5	−18.0
FROM	−1.09	3.26	−0.22	1.76
Hidden node # 3				
BIAS:	16.8			
TO:	−7.42	−53.6	−6.18	−7.28
FROM:	−1.06	−5.99	−6.03	−4.84
Hidden node # 4				
BIAS:	−3.79			
TO:	−26.4	−0.69	13.5	−11.6
FROM:	2.54	−2.17	−2.30	1.31
RECOMM				
BIAS:	0.61			
TO:	−1.00	−1.09	−1.06	2.54
SATIS				
BIAS:	0.26			
TO:	−0.38	3.26	−5.99	−2.17
USAGE				
BIAS:	1.09			
TO:	−0.35	−0.22	−6.03	−2.30
CONTINUE				
BIAS:	0.53			
TO:	0.09	1.76	−4.84	1.31

After analysing the functionality of the neural model, as shown in the figures above, the following conclusions were drawn:

- Assumed functional risks concerning the usage of ATMs held the maximum weight contribution. After that came the formation of service expectations, financial risk, and client confidence.

- Previous expectations and a former discernment of financial risk when using ATMs did not significantly influence user innovativeness.

- Consumer risk identification demonstrated the strongest connection - a reversed correlation to the perceived quantity of functional risk, – financial risk, and level of confidence. This construct additionally displayed a positive connection to consumer expectations.

▪ It was established that situational contingent factors[73] could possibly be interconnected and influence expectations and confidence negatively, as well as to strengthen clients' perceptions of risks.

▪ The extent of cognitive analysis was found to assist in the reduction of beliefs of risk and the formation of service expectations, as well as to enhance consumers' levels of confidence when using ATMs.

▪ The analysis showed that clients who perceived themselves as innovators, – were challenged with identifiable contingencies, and believed in a high level of risk, will not advocate ATM-usage to others. Trendsetters will probably try new functions on the machine, and this will influence their service expectations. Situational contingencies, as well as the consumer's level of cognitive activity and behavioural effort can also cause service dissatisfaction. On the other hand, methods employed by the client to cut risks can enhance user satisfaction.

▪ It was also concluded that a deficiency in risk-reduction strategies, situational contingencies, cognitive activity, and behavioural efforts could decrease ATM-usage; while user innovativeness could have the opposite effect. A consumer's objective to re-use an ATM can be boosted by user innovativeness, the employment of risk-reducing tactics, and information-processing and -evaluation levels.

▪ Lastly, it was concluded that the re-usage of ATMs could only be inhibited by particular situational contingencies.

Although the calculations and analysis of results drawn from this case are legitimate due to the significance of the associations between the differences, notwithstanding of the specific constants chosen, the conclusions are a bit constrained because variables were only measured once. Andreasen (1977) claimed that the process of satisfaction formation happened over a prolonged period and therefore should preferably be measured over time. Nevertheless, Mouthino et al. argued the results of their study to be satisfactory, although further experimentation on this theme, focussing on additional causes of consumer satisfaction, are in order.

The outcomes from this case showed that an abundance of conclusions can be derived from a single study when using ANNs to analyse data. The example also demonstrated the possibility to identify and examine several concealed constructs that would otherwise be ignored or impossible. The model displayed here possibly enclosed more information than the experimenters originally aimed for.

---

73 Examples of situational contingencies include non-habitual ATM usage location and clients' perceptions of technical doubts.

5.2 A MUSICAL NETWORK MODEL TO USE AS RESEARCH TOOL IN SOUTH AFRICAN ADVERTISEMENT MUSIC

5.2.1 Research problem and design of the model

The author of this thesis undertook to invalidate Woodward's claim[74] that there does not exist a formula, style, or technique that can secure the functionality of a musical commercial – in presenting a tool that can actually guarantee this to some degree. Thus, the following methodology and ensuing model addresses the hypothesis presented in the introduction to the thesis: *functional commercial music can to a certain extent be guaranteed – in musical terms and through the application of well-considered and empirically proven musical elements – in a specified context.*

To reiterate, a *specified context* refers to advertisement music aimed towards a multicultural South African society, and to all commercials where music accompanies a visual scene - such as television advertisements and cinematic commercials. Excluded are advertisements where only sound is used as the main advertising medium, such as radio commercials. *Functional commercial music* implies the following: music which has relevance to, and is in fitting with, a unique product; music which plays a supportive and complimentary part in the advertising of a product; and music which effectively addresses the target-group – in that it has the relevant emotional effect on the specific culturally-specified target population, which fits the marketing goals of the advertising agent.

Taking a multidisciplinary point of view, the author suggests a methodology for the design of a tool in the form of a musical network model. This model can possibly confirm that the amalgamation of scientific findings from numerous fields of study could – and should – play a significant part in the composition and assessment of effective, target-group-specific advertisement music. On the whole, the scenario is based on the four research questions presented in the introduction to the thesis:

1 Do various groups in South Africa (hereafter referred to as target groups) reveal homogeneous patterns of affective reactivity to advertisement music?
2 If so, is this reaction in fitting with the goal of the advertisement?
3 Based on the knowledge of these goals, can universals be established in the emotional response of homogeneous target groups to advertisement music?
4 If so, could this knowledge be helpful in the assessment and composition of functional advertisement music?

[74] Presented in the introduction to the thesis.

Thematically, the intended model focuses on the implications of advertisement music's emotional and cognitive effects on consumers. The following variables – which constitute the input neurons of the network – are considered: psychological affect, cognitive reaction, personal opinion, perception of the suitability of music, short-term memory recall of the musical cues, familiarity to the tonal system, and buyer's intention. Given that several of these variables have an abstract disposition and could not be measured directly for the purposes of this study,[75] these constructs had to be observed indirectly by reviewing empirical studies and theoretical contributions presented throughout the thesis. In particular, pertinent research done in the fields of Psychology- and Social Psychology of Music (including film music studies), Consumer Science, the Cognitive Sciences (including the Neuropsychology of Music, Cognitive Psychology, and Systematic Cognitive Musicology) were considered in this regard. These empirically conducted theoretical contributions, as presented in the qualitative theoretical reviews of Chapter 1 and the literature review of Chapter 4, had already been proven as valid and reliable, and had been used as secondary units of data in the present study.

The methodological conceptualization underlying the development of the musical model is twofold. It encompasses an empirical secondary data analysis in reanalysing existing data to test hypotheses and validate models. Secondly, it employs this information in a computer simulation aimed at creating and validating an accurate representation of people's perception of the world (in this case, advertising music).

In the proposed model, an ANN will be used as a tool to examine relationships between variables and to establish the strongest connections regarding these associations. If the most significant input units can be ascertained in this way, this knowledge can be utilized in future research, to build advanced models by using actual data. Therefore, the decisive measurement of the success of the proposed model can only be done in a future study, by evaluating its ability to actually find the strongest associations between input- and output variables whilst using actual data. If it can be established that the proposed model can indeed operate successfully in this way, it would have reached its ultimate goal of assisting in the prediction of an optimal match between consumer target groups and functional advertisement music.

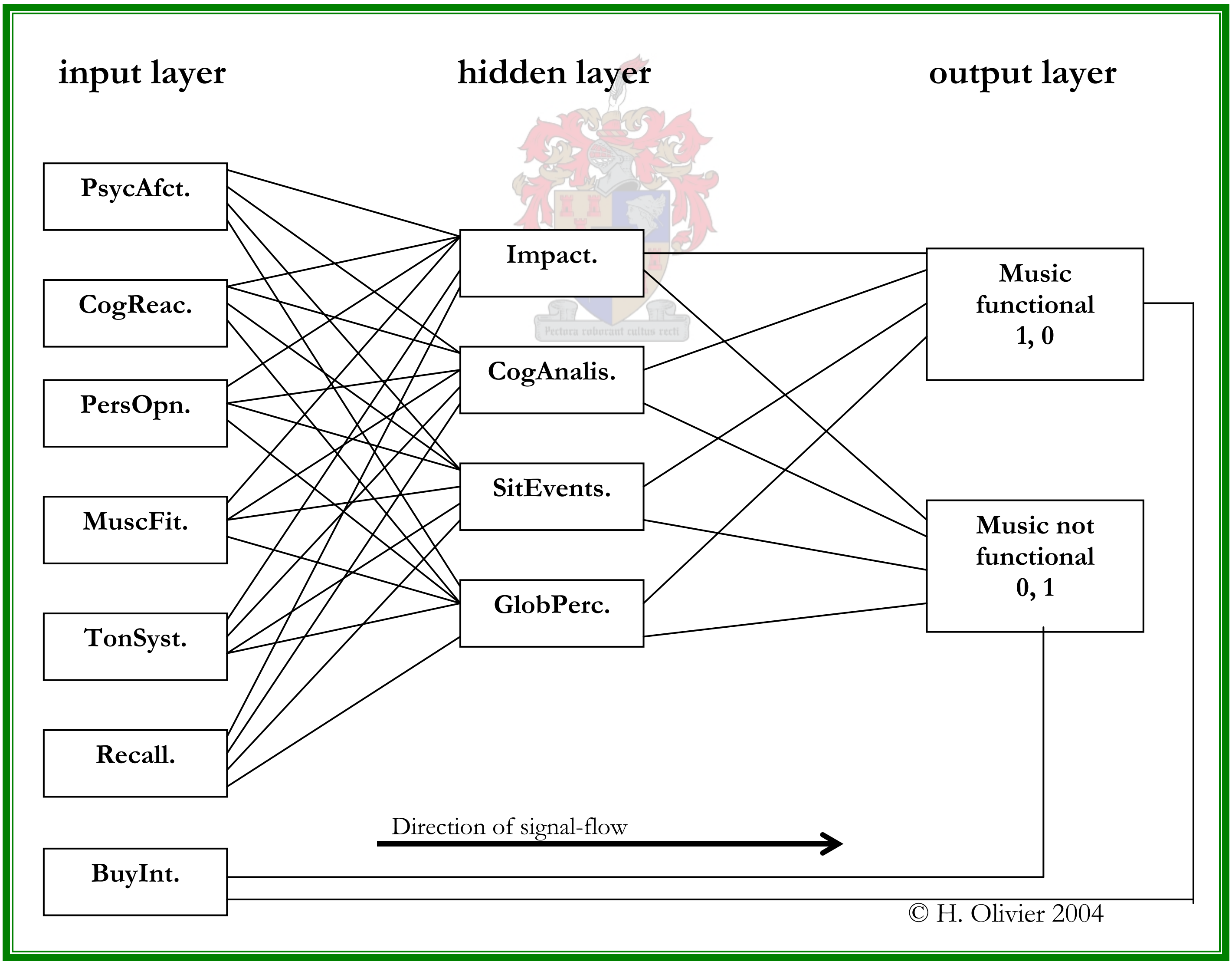
[75] An investigation of such a degree falls outside the scope of this Master's thesis. Refer to the final chapter on future directions for som

e prospects and endeavours in this regard.

5.2.2 The proposed musical network model and network architecture

The architecture chosen for this application is a multilayered, feedforward network - as illustrated in figure 5.4. The backpropagation learning algorithm will be employed. By analysing responses to a questionnaire, the respondents' cognitive and emotional reactions to the advertisement music, correlation of these reactions to the goal of the commercial, and probable buyer intentions are established. These constructs are accordingly associated with the suitability of the advertisement music. Four of these constructs are measured implicitly through the hidden neurons. Two output units are used, identified as *functional advertisement music* (1,0), and *non-functional advertisement music* (0,1). An important feature of the suggested neural model is that it is persistently flexible and extendable. Thus, novel information, ideas, trends or research predilections from any additional fields which might become available in future, can easily be included as additional input- and hidden neurons in the model.

Figure 5.4 The Musical Network



The seven dependent variables, which serve as the inputs to the network, are classified and conceptualized in the following way. References to correlating sections are included in the description.

5.2.2.1 Input neurons (dependant variables)

Psychological affect (PsycAfct.): A subjective account of the degree of affective reaction (feelings, emotions and moods) induced by the advertisement music.

- **Measurement:** Experimentally measured in the questionnaire (phase 1). The neuron can take the value of 1,0 (high degree of affect) or –1,0 (low degree of affect).
- **References:** Sections 1.1; 1.2.1; 1.2.2; 4.1.1; 4.1.3; 4.2.

Cognitive reaction (CogReac.): An objective measurement of the degree of neural activity, with a focus on level of arousal (measured as alpha blocking in the brain).

- **Measurement:** Measured by an EEG, phase 2 on the questionnaire. The neuron can take the value of 1,0 (high degree of arousal) or –1,0 (low degree of arousal).
- **References:** Sections 1.2.3; 1.2.4; 1.3; 4.1.2.

Personal opinion (PersOpn.): Respondents' subjective report on their amiability and enjoyment of the music – related to genre, style, compositional techniques, etc.

- **Measurement:** Measured by Phase 3 on the questionnaire. The neuron can take the value of 1,0 (likeable) or –1,0 (not likeable).
- **References:** Sections 1.2.1; 1.2.2; 1.3.3; 4.1.1; 4.1.3

Suitability of music (MuscFit.): Respondents' views on the appropriateness of the advertisement music to the product being advertised. This variable is related to the establishment of the commercial's authority, credibility, and effective communication of meaning.

- **Measurement:** Measured by Phase 4 on the questionnaire. The neuron can take the value of 1,0 (suitable) or –1,0 (unsuitable).
- **References:** Sections 1.1.2; 4.1.1; 4.1.3; 4.2.

Tonal system of the music (TonSyst.): The prevailing tonal system of the music, and the respondents' degree of familiarity with the specified tonality. A variety of Western- and non-Western tonalities were used, trying to assess if unfamiliar tonalities would have a significant effect on listener's perception and recall of commercials.

- **Measurement:** Measured in phase 5 on the questionnaire. The neuron can take the value of 1,0 (respondent is familiar with the tonal system) or –1,0 (respondent finds the tonality exotic).
- **References:** Sections 1.1; 4.1.1; 4.1.2; 4.1.3.

Remembrance of music (Recall.): The degree of respondents' remembrance of advertisement music, linked to the specific product being advertised.

- **Measurement:** After the 10 commercials were presented to the subjects and the questionnaire had been completed, the subjects were given a 15-minute break. They were subsequently called in again and presented with the advertisements' music alone, in absence with visuals. The subjects were asked if they could remember which product was linked to each segment of music (Phase 6 on the questionnaire). The neuron can take the value of 1,0 (respondent could associate the product with the music) or –1,0 (respondent could not associate the product with the music).
- **References:** Sections 1.2.1; 1.2.4; 4.1.1; 4.1.3; 4.2.

Intention to buy (BuyInt.): Respondents' likelihood of purchasing the specified product if it was advertised in this way. Intention to buy is a very strong factor in the assessment of the functionality of an advertising campaign – therefore, this input unit is given a stronger connection in this network and a direct link to the output layer.

- **Measurement:** Phase 7 - respondents were asked to try and focus on the success and credibility that the advertising medium achieved, and not on qualities related to the particular product itself. The neuron can take the value of 1,0 (intention to buy) or –1,0 (no intention to buy).
- **References:** Sections 4.1.3; 4.2.

5.2.2.2 Hidden neurons

Four units are included in the hidden layer:

Overall impact (Impact.): The degree of cognitive and emotional impact that the advertisement had on the respondent in general. If the impact is high, the respondent had been influenced to a high degree, and the product will most probably be given more attention in the future. This could lead to a higher degree of buyers intention.

- **References:** Sections 1.1; 1.2.1; 1.2.2; 1.2.4; 4.1; 4.2.

Consumer's cognitive analysis (CogAnalis): The quantity of processed and evaluated information regarding musically-paired advertisements in general. This data is stored in the subject's long-term memory and can influence the subject's current judgement of advertisements.

- **References:** Sections 4.1; 4.2.

Situational eventualities (SitEvent.): Variables that are produced by factors outside of the experimenter's control, which influence the respondent's decision regarding the product. These may include previous experiences with advertising, or any positive or negative feelings towards a specific product born from personal experience.

- **References:** Sections 1.2.1; 1.2.2; 4.1; 4.2.

Global perception of the commercial (GlobPerc.): The general positive or negative perception of the advertisement – this evaluation is made subjectively by the respondent. If an advertisement is generally perceived as positive, the likeability of a purchase is increased.

- **References:** Sections 4.1; 4.2.

Many additional endogenous constructs could also be recognized or inferred from a model similar to this one. However, to keep this example simple and manageable, these are not included in this instance.

5.2.3 Encoding the model

To use the suggested model as a tool that can recognize and analyse information regarding South African advertisement music, it needs to be encoded in a digital environment - such as a neural network software program. The following section provides a brief overview of the methodology underlying the programming of the suggested model in the chosen medium – MATLAB®'s Neural Network Toolbox.[76]

According to the manufacturers of MATLAB®, The MathWorks, Inc. (2001) - MATLAB® is a *high-performance language for technical computing*. MATLAB® (matrix laboratory) is an interactive system which basic data constituent is a display that does not necessitate dimensioning. This implies that users are able to solve numerous technical computing problems - in particular those with matrix and vector formulations – a great deal faster than it would take to write a program in a scalar noninteractive language such as *C* or *FORTRAN*.

[76] For a comprehensive tutorial regarding the creation of a neural model in the MATLAB® Neural Network Toolbox, the reader is referred to Demuth & Bearle (2001).

The MATLAB® software integrates computation, visualization, and programming in a user-friendly environment where problems and solutions are expressed in common mathematical notation. A few uses of MATLAB® include mathematical computation; modeling, simulation; data analysis; exploration and visualization; scientific and engineering graphics; and algorithm- and application generation (such as the creation of graphical user interfaces). MATLAB® offers a collection of application-specific *solutions* called *toolboxes,* which allow users to learn and apply specialized technology. Toolboxes are comprehensive collections of MATLAB functions which extend the MATLAB® milieu to solve specific categories of problems. There are numerous toolboxes available in the MATLAB® environment, such as the signal processing toolbox, control system toolbox, fuzzy logic toolbox, simulation toolbox, and the Neural Network Toolbox. The Neural Network Toolbox is a set of MATLAB functions for the *design, implementation, visualization, and simulation* of neural networks (The MathWorks, Inc. (2001)). It supports an extensive variety of network architectures with an infinite amount of processing elements and interconnections.

The initial step in simulating the specified model in the Neural Network Toolbox is to program a new network in the toolbox's graphical user interface (GUI). In this space, users are able to *create networks; enter data into the GUI; initialize, train, and simulate the networks; export training results from the GUI to the command line workspace; and import data from the command line workspace to the GUI.* The toolbox can deal with numerous types of different networks and architectures. Figure 5.5, cited from Demuth & Bearle (2001: 378), describes the language codes used to generate the standard functions in the GUI.

By selecting one of these functions and programming it in the GUI, the user specifies the chosen network's architecture - such as the selection of the number of inputs, outputs, layers, and the type of connections between them. The format of input data structures influences the simulation of the network. In the proposed example, the input vectors do not occur in any particular time sequence. For such concurrent network types, the order of inputs is irrelevant – this simplifies the generation of the model. The musical network also does not have any feedback- or delay inputs.

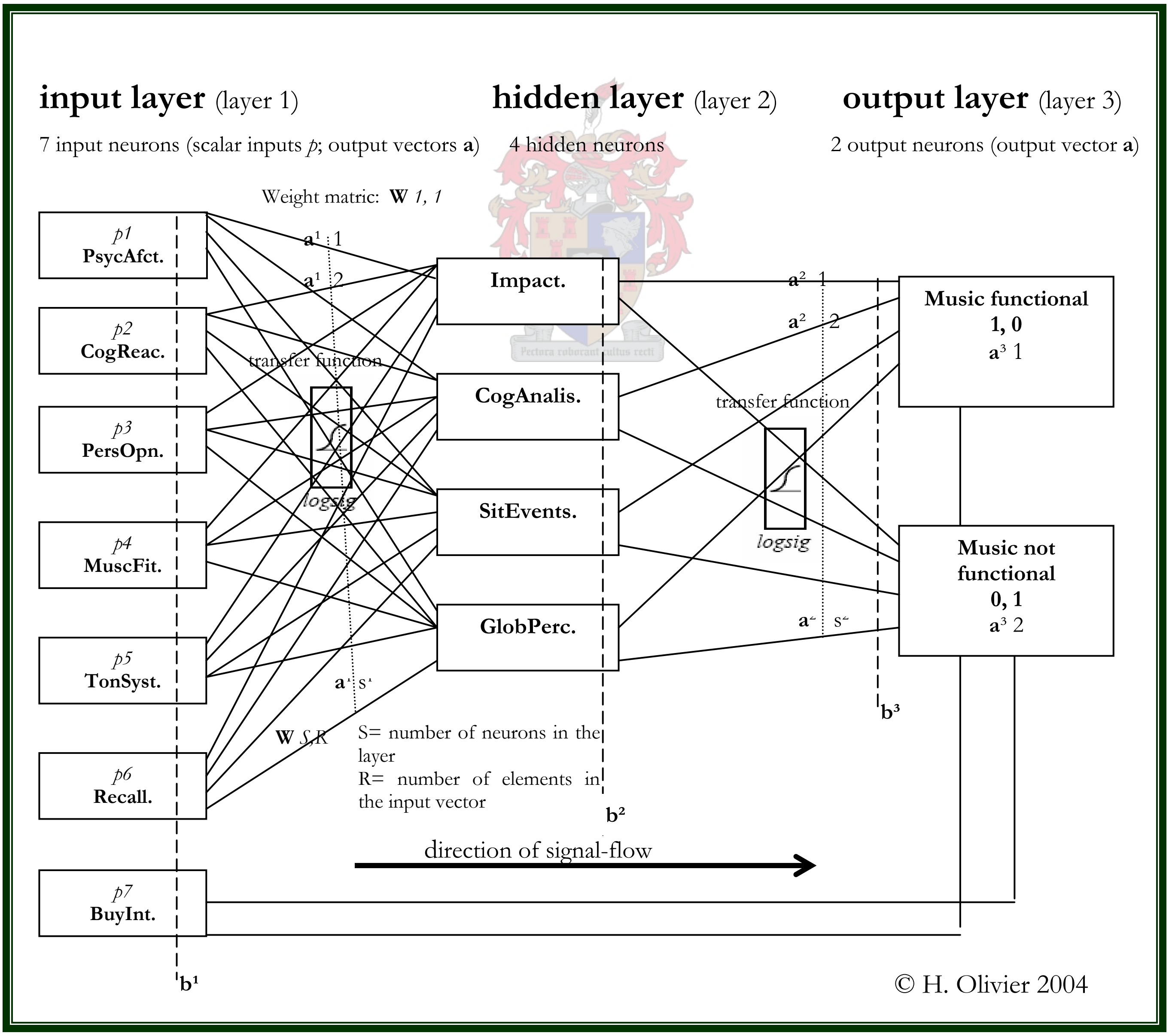
Figure 5.5 The standard MATLAB® Neural Network Toolbox creation functions

New Networks	
`newc`	Create a competitive layer.
`newcf`	Create a cascade-forward backpropagation network.
`newelm`	Create an Elman backpropagation network.
`newff`	Create a feed-forward backpropagation network.
`newfftd`	Create a feed-forward input-delay backprop network.
`newgrnn`	Design a generalized regression neural network.
`newhop`	Create a Hopfield recurrent network.
`newlin`	Create a linear layer.
`newlind`	Design a linear layer.
`newlvq`	Create a learning vector quantization network
`newp`	Create a perceptron.
`newpnn`	Design a probabilistic neural network.
`newrb`	Design a radial basis network.
`newrbe`	Design an exact radial basis network.
`newsom`	Create a self-organizing map.

The following mathematical notations are to be used when programming a network in the Neural Network Toolbox: Scalar inputs are written as small italic letters (e.g. *a,b,c)*, and vectors (a column of numbers) are small, bold non-italic letters, such as **a,b,c**. Matrices are distinguished by capital, bold, non-italic letters (**A,B,C**). A single superscript is employed to recognize the elements in a layer. For example, the net input of layer 2 would be shown as **n**2. Superscripts are used to identify the source link and destination connection of layer weight matrices and input weight matrices.

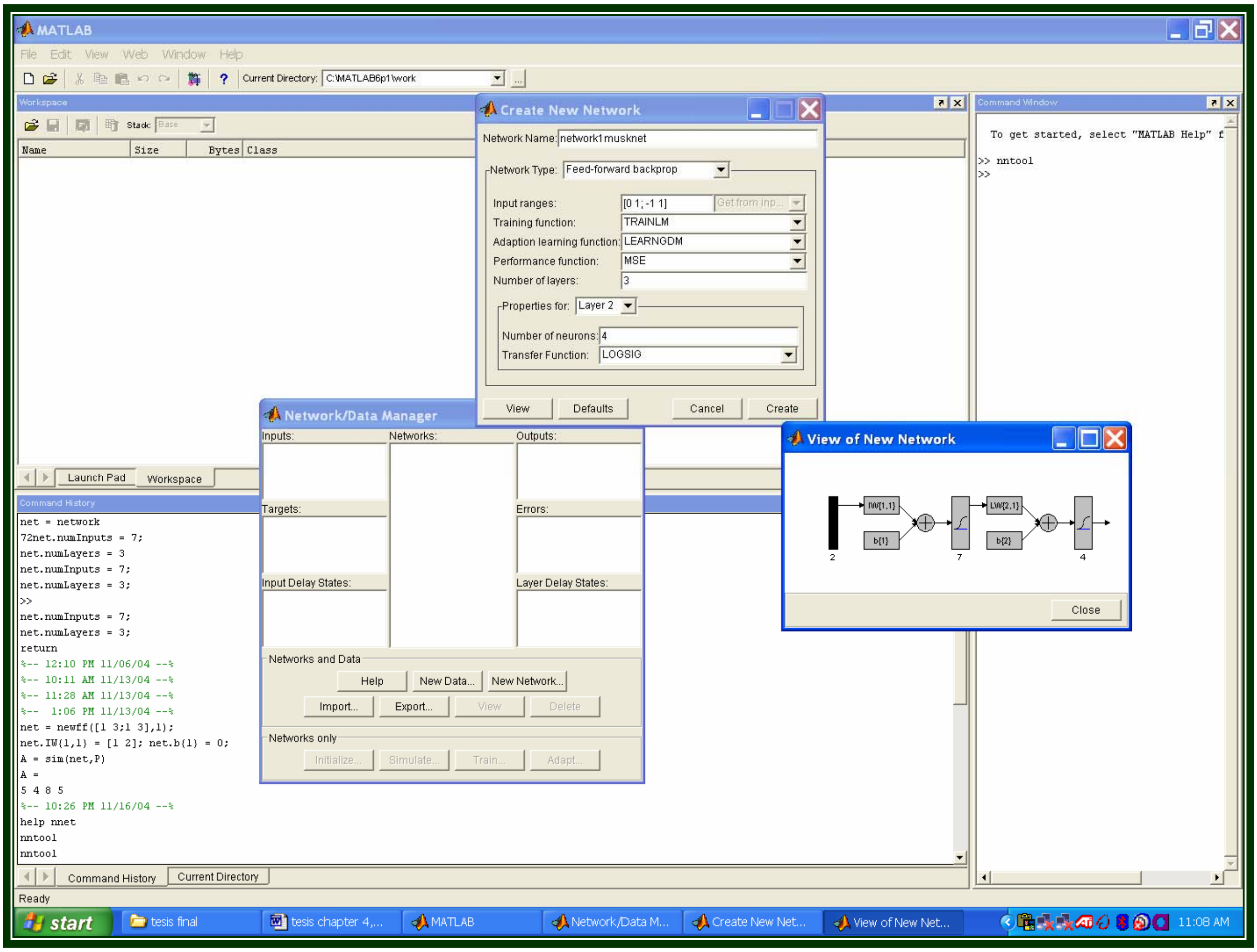
The musical network has 3 layers, each with a weight matrix **W**, a bias vector **b**, and an output vector **a**. The outputs of each middle layer can be seen as the input neurons to the following layer, implying that layer 2 can be described as a one-layer network with S1 inputs, S2 neurons, and an S2xS1 weight matrix **W**2. The input to layer 2 is **a**1 and the output is **a**2. If you identify all the vectors and matrices of layer 2, for example, it can be dealt with as an independent single-layered network. This approach can be taken with any layer of the network, making the conceptualization of its functionality relatively straightforward. In the MATLAB® Neural Network Toolbox, all the layers except the final one which computes the output of the network as a whole, are identified as hidden layers. Thus, the musical network has one output layer (layer 3) and two hidden layers (layer 1 and layer 2), with a total of 11 inputs (S1(7) neurons in the first layer, and S2(4) neurons in the second layer). A bias vector **b**, with a constant input of 1, has been included in the proposed model. As **W** and **b** are both adjustable scalar parameters of the neuron, these parameters can be adjusted so that the network demonstrates a preferred behavior. In this way, by adjusting the weight or bias parameters, the network can be trained to do a particular desired task. Subsequently, all of these concepts are incorporated in the musical model and the final product illustrated in figure 5.6.

Figure 5.6   Initiating the musical network model in MATLAB®'s Neural Network Toolbox



MATLAB®'s Neural Network Toolbox gives the user the option to enter the command *nntool* when programming in the GUI. The author used this tool to obtain the following graphics of the musical network.

Figure 5.7 A view of the musical network in MATLAB®'s Neural Network Toolbox



5.2.4 Suggested methodology for the collection of actual data as training sample[77]

To be able to use the suggested model as a tool to establish if the advertisement music effectively addresses the target population - in that it has the relevant emotional effect on the specific culturally-specified target population which fits the marketing goals of the advertising agent - the author proposes a few guidelines to be considered in this regard.

Following the conceptualization of the specific aim of the application, a training sample should be collected which fits the target group in question.[78] The selected subjects should match the specified target group, and can be selected by means of a non-probability quota sampling technique.[79] The experimenter must strive to, as far as possible, select products which are not explicitly dispositional to the identified target group.[80]

A multifaceted measurement[81] should be made of the subjects' responses, after exposing them to the chosen advertisements. The musical segments should be presented in random order. In this regard, a comprehensive questionnaire is suggested to use as measuring instrument. The questionnaire must be compiled in an interdisciplinary manner by combining methodologies from the identified paradigms. A suggested simplified model of the main topics dealt with in the questionnaire is presented in fig. 5.4.

The recommended procedure of pre-processing the data collected in the questionnaire is 1-out-of-N encoding, which will convert the categorical data to columns of binary variables. In regard to the questionnaire at hand, the binary sequence will largely ensue automatically as a result of the qualities of the questions and multiple choice options.

---

[77] Note that all assumptions regarding data, e.g. inputs and outputs, assumptions are based on hypothetical assumptions based on evidence presented in the identified literary reviews, and are – for the sake of this endeavour – perceived as empirically valid and trustworthy.

[78] Attention should be paid to constructs such as cultural norms, age groups, socio-economic groups, and gender groups.

[79] The subjects might be motivated to participate by awarding them with a month's free subscription to a television channel, sponsored by a local broadcasting company.

[80] For example food, clothes, travel, general well being.

[81] Containing both qualitative and quantitative analyses of the raw data from the questionnaire.

Figure 5.5: Prototype of a measuring instrument: questionnaire

Phase 1 (qualitative measurement) - measures psychological affect

Determines if the advertisement music influences the respondent's current emotional state and mood, and whether this is a strong reaction. This section includes a list of adjectives that the respondent is asked to pair with the music. (Measured as high psychological affect / low affect).

Phase 2 (quantitative measurement) - measures cognitive reaction

An objective measurement of the degree of neural activity within the respondent's brain, with a focus on arousal (alpha blocking). Measured by an EEG, as high or low arousal

Phase 3 (qualitative measurement) - measures personal opinion

Establishes if the subject liked the style, melody, instrumentation, rhythm, and overall 'feel' of the music. (Yes/ No).

Phase 4 (qualitative measurement) - measures suitability of music

Respondents' views on the appropriateness of the advertisement music to the product being advertised. The questions are related to the establishment of the commercial's authority, credibility and ability to effectively communicate meaning. This phase also determines if the respondent thinks that the music fits the product being advertised. (Yes/ No).

Phase 5 (qualitative measurement) - measures respondents' familiarity with the tonal system

Established by means of questions aimed at determining the respondents' degree of musical training and familiarity with the tonality of the musical cues. (Yes-respondent is familiar with the tonal system / No - respondent find the tonality exotic).

Phase 6 (quantitative measurement) - **measures recall**

Ascertains the subjects' short-term memory recall of the music after a short time interval of 15 minutes. Subjects are presented with the advertisements' music alone, in absence of any visual material. The subjects are asked if they can remember which product was linked to each segment of music. (Yes- respondent can associate more than 5 of the product with the correct musical cue / No- respondent fails to associate 5 or more of the product with its correlating music).

Phase 7 (qualitative measurement) - measures buyer intention

Respondents are asked to try and focus only on the degree of credibility that the advertising medium contributed to the product, and not on qualities related to the particular product itself. The questions determine any intention to buy the product due to successful advertising. (Yes- intention to buy / No - no intention to buy).

As previously explained, the decisive measurement of the success of the proposed musical network can only be made in a future study, after importing the actual data obtained from the questionnaire into the network, and assessing the network's behaviour on receiving these data inputs. The model should be able to learn the attributes of the data, and to generalize the relationships discovered to new data. By comparing the model to similar networks used in the industry[82], the author cannot anticipate any reason why - in theory as well as methodologically - the suggested network should not be able to be successfully employed for its intended purposes.

References

Altman, E. I., Marco, G. & Varetto, F. (1994). Corporate distress diagnosis: comparisons using linear discriminate analysis and neural networks. ***Journal of Banking and Finance,*** (18), 505-529.

Andreasen, A. R. (1977). A Taxonomy of consumer satisfaction/dissatisfaction measures. ***Journal of Consumer Affairs,*** (11), 1-24.

Baum, E. B. (1988). Neural Nets for Economists. In Anderson, P.W. et al (Eds.). ***The Economy as an Evolving Complex System,*** 33-48. Redwood City, CA: Addison-Wesley.

Barr, D.S. & Mani, G. (1994). Using neural nets to manage investments. ***AI Expert,*** (9), 16-21.

Beltratti, A, Margarita, S. & Terna, P. (1996). ***Neural Networks for Economic and Financial Modelling.*** London: International Thompson Computer Press.

[82] Refer to sections 2.5; 3.4; 4.1.2; 5.1.

Boritz, J. & Kennedy, D. (1996). ***Effectiveness of neural-network types for prediction of business failure.*** Unpublished doctoral dissertation, University of Waterloo.

Carter, C. & Catlett, J. (1987). Assessing credit card applications using machine learning. ***Journal of Marketing,*** (46), 82-91.

Demuth, H. & Beale, M. (2001). **Neural Network Toolbox Users Guide Version 4.** The MathWorks, Inc.

El-Temtamy, O. S. (1995). ***Bankruptcy prediction: a comparative study on logit and neural networks.*** Unpublished doctoral dissertation, Middle Tennessee State University.

Gately, E. (1996). ***Neural Networks for Financial Forecasting.*** New York: John Wiley & Sons.

Harston, C. T. (1990). Business with Neural Networks. In Maren, A., Harston, C. & Pap, R. (1990). ***Handbook of Neural Computing Applications,*** (391-407). San Diego, California: Academic Press, Inc.

Kennedy, M.S. (1991). Artificial intelligence in media planning: an exploration of neural networks. In Gilly et al (Eds.). ***Enhancing Knowledge Development in Marketing*** (***Proceedings of the American Marketing Association Educators' Summer Conference),*** (390-397). Chicago, Illinois: American Marketing Association.

Kong, J. H. L. & Martin, G. M. (1995). A backpropagation neural network for sales forecasting. ***Proceedings of the IEEE International Conference on Neural Networks,*** (2), 1007-1011.

Margarita, S. (1991). Neural Networks, Genetic Algorithms and Stock Trading. In Kohonen et al (Eds.). ***Artificial Neural Networks.*** Amsterdam: North-Holland.

Moutinho, L., Curry, B., Davies, F. & Rita, P. (1994). ***Computer Modelling and Expert Systems in Marketing.*** London: Routledge.

Smith, K.A. (1999). Introduction to Neural Networks and Data mining for Business applications. South Melbourne, Australia: Corporate Printers.

The MathWorks, Inc. (2001). ***Neural Network Toolbox.*** Retrieved November 20th, 2004 from the World Wide Web: http://www.mathworks.nl/products/neuralnet/description1.jsp

Wong, B. K., Bodnovich, T. A. & Selvi, Y. (1995). A bibliography of neural network business applications research: 1988- September 1994. ***Expert Systems,*** (12/3), 253-261.

Zirilli, J. S. (1997). Financial Prediction using Neural Networks. London: ITP.

CONCLUSION AND FUTURE DIRECTIONS

Woodward[83] claimed that there are no musical methods which can secure a successful musical commercial. Although his description of well-designed advertisement music reflects a lack of scientifically valid and reliable research in this field, it should not be overseen that he is still one of a very few scholars whom actually gave the subject of advertisement music any serious consideration at all. This thesis explored the notion that knowledge from various interdisciplinary study fields can, and ought to, play a leading role in the creation and assessment of effective, target-group-specific advertisement music. In obtaining this goal, it examined the probability of producing a computer-based tool which can assist people working in the advertising industry to obtain a better and more educated match between product, consumer, and advertisement music. In the undertaking of this endeavour, the notion is consequently validated that the field of advertisement music is indeed deserving of greater scientific consideration, and should be recognized as such in future.

The main initiative of this pilot study was to establish if one can, in any way, guarantee the functionality of a musical commercial in any given context. If you have access to actual records of the homogeneous patterns of affective reactivity to South African television advertisement music, which are in fit with the goal of the advertisement, and therefore can establish universals in the emotional response of homogeneous cultural groups to advertisement music[84] – this information can indeed be applied in a music technological context to assist in the assessment and composition of functional advertisement music. By using a musical network, it is certainly possible to guarantee a functional musically-paired commercial, which effectively addresses its target-group and has an appropriate emotional effect in support of the marketing goals of the advertising agent.

In addition to this, the thesis demonstrated that it is possible to gain original and innovative interpretations and insights regarding a fairly unstudied discipline, without necessarily conducting new research studies in the specified field. This is feasible by combining knowledge which had been acquired before in other fields, even if these studies' areas of applications are significantly distinct from

---

[83] Refer to p.2.

[84] Obtainable through empirical studies.

one another and the target field. The author demonstrated that - by taking an interdisciplinary approach and by using ANNs - it is possible to attain new data that is scientifically valid, even in a supposed *unempirical* field such as South African advertisement music. Even though this research endeavour merely presented a preliminary exploration of these ideas, hopefully the concept has been thoroughly rooted that an interdisciplinary approach has a lot to offer in this field, and also to music research in general.

In conclusion, although the scope of the thesis did not provide for the actual implementation of the musical network (due to the lack of relevant data form the field), the feasibility of the conceptual idea was thoroughly examined, and it is therefore concluded that the theory in its entirely is definitely practical, and can as such be implemented in a future study.

FUTURE DIRECTIONS

The prospect of a superior understanding of human cognition - in particular the complex relationships between cognition, emotional states, reasoning and decision making - sounds very promising indeed. It is perhaps not too farfetched to imagine that such a comprehensive understanding could possibly result in an ability to make meaningful predictions concerning man's behaviour – such as his reaction to advertisement music – even though this idea rather resembles those fabricated by scriptwriters at Hollywood's science fiction department.

Countless scientists had been struggling for centuries to find a significant connection between cognition, emotion and reasoning – resulting in today's rather embarrassingly imperfect understanding of even the most basic human cognition. We should apprehend that it is unlikely that major breakthroughs in the Cognitive Sciences, Psychology, Sociology or the Medical Sciences will elucidate everything about the human brain and -behaviour in the very near future. We will probably never fully understand the functionality of the humanoid nervous system in its totality. Realizing this, we should transfer our attentions to constructs that we currently know and understand. To begin with, we could reconsider the power that lies in the integration of diverse results and an interdisciplinary perspective in research. Using the tools we have to our disposal at the moment – digital tools such as ANNs which did not exist a few decades before – this is actually effortlessly attainable today.

This thesis demonstrated that it is readily feasible to break those traditional boundaries that have periodically prevented the Humanities and the Natural Sciences to join forces towards a greater understanding of man. By using ANNs, we are able to merge data from the Humanities and Natural Sciences; Philosophy and Neuroscience; Psychology and Artificial intelligence; Musicology and Computer Science; and Sociology and Neuropsychology – to name but a few of the countless possibilities – in a single enterprise. Surely, the results, interpretations and applications which could develop from these studies would be far more inclusive than those derived from research conducted in only one or two of these fields in isolation. The possibilities and power that lie in such research, combined with the knowledge that could be born from these endeavours, is almost limitless. Furthermore, it is almost unimaginable to actually use this power that is knowledge in a money-driven field such as advertising.

This thesis made it very clear that artificial neural network models present scholars with a tool which has been proven to be successfully applied in many research problems. ANNs frequently surpasses standard exploratory procedures, and is also much suitable for indistinct data environments – such as those frequently encountered in the Social Sciences. As stated before, neural network models often outperform traditional statistical procedures where problems lack discernible structure, where data is incomplete, and where the formulation of structural equations is impossible. As neural network models are universal, non-parametric and robust, they are particularly applicable to data which is noisy, overlapping, non-linear and non-contiguous – similar to those encountered in advertisement music research. Since there is also no limitation on the amount of input variables in such models, ANNs are perhaps the perfect solution for scholars of advertisement music. It is palpable that researchers in the broader domain of Musicology should also recognise the many advantages of this methodology, and exploit artificial neural network methodologies to a greater extent in future research.

By employing ANNs as research tool, advertisement music – a discipline which is typically perceived as unworthy of any serious pragmatic scientific study – can obtain credibility as a field worthy of empirical study. Furthermore, if scholars paid more attention to this field due to its newfound authority, the economic implications and enormous marketing potential of such endeavours will surely be realized. This could serve as propaganda to advertise this unacknowledged and unacademic field as being much more worthy of study – resulting in its being a noteworthy discipline with its own set of paradigms and testable theories.

In the same way, an abstract field such as Musicology could become much more assessable for scholars from other disciplines, even from the Natural Sciences – in being contemporary in its method and addressing more relevant issues. The employment of tools inherent to the Natural Sciences in a field such as advertising music or any other division of Musicology, could be perceived by some traditionally-bound scholars as improper or even revolutionary. However, it is the author's belief that a methodology such as ANNs can assist greatly to position a rather elitist discipline, like Musicology, more prominently on the academic map.

As thoroughly revealed throughout this thesis, advertisement music is of great concern to many people related to the business sector, and especially to those concerned with the marketing of products. There is no argument against the statement that marketing in its many facets is probably one of the greatest economic powers in the modern world. Companies spend fantastic amounts of money on the marketing of their products alone. Very few of these marketing campaigns ever go unaccompanied by a form of sound or music. ANNs have already been successfully applied in a variety of areas within the scope of Economics and Business. These models have, amongst others, been used in the modelling of consumer choice and production functions; target marketing; document retrieval; employee classification- and selection; bankruptcy prediction; economic modelling and decision-making; risk assessment; stock selection and sales forecasting; trading and financial forecasting, loan applicant decision making, and financial fraud detection.

In addition to these, this thesis argued for their application in advertisement music research. By approaching the study of advertisements through an ANN perspective, scientific research findings and interpretations could become readily available. There is thus no reason why, in future, the findings from ANN methodologies in advertisement music research cannot be practically applied by companies for guaranteed success in their advertising campaigns.

To be able to attain all of the former ideas and visualizations in the field of advertisement music, the most pressing and immediate future direction is for the realization and implementation of the musical network, as it is presented in the final chapter. The author therefore suggests a study to obtain the necessary data concerning South African advertisement music – by using a methodology similar to that suggested in section 5.2.4. Having attained this knowledge, it can be entered into the suggested musical network, the networks behaviour can be asserted, and findings can finally be implemented.

Although merely a glimpse of the thinking that motivates the construction of a musical network model was put into words in this endeavour, it should be clear that the basic idea is, or can potentially be, much more advanced than this author's modest attempt. Of course it is true that ANNs have their shortcomings – similar to any research methodology – and are by no means the Messiah of the research and data mining world. Nevertheless, the capacity of a single tool such as the musical network presented in this thesis, should tempt even the most traditional and theory-bound scholar to at least consider it.

This thesis is clearly in support of a paradigm shift towards interdisciplinarity in Musicology, which the study of advertisement music undeniably forms a part of. It also argues strongly for the case of a neural network methodology in this field. By using this simple software program that runs on a standard PC, much power lies in the hands of any interested scholar in this field, for whatever reason she may fabricate.